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Selection of traceability-based, automated decision-making methods in global production networks

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Abstract

Automating traceability-based decision-making can shorten the reaction time to supply chain disruptions. This paper develops a framework for choosing automated decision-making (ADM) methods based on traceability data. It contains a toolbox comprising methods suitable for ADM, respective selection criteria and a new process to select a suitable ADM method based on companies' requirements. This process is based on an evaluation matrix matching methods and criteria. As a result, the ADM framework suggests the most suitable method to automate a specifically chosen decision. The developed framework is validated in the supply chain of a globally operating truck manufacturer.

Keywords: Automated decision-making; framework; global production networks; traceability; supply chain; method selection; data; decisions; production; adaptable PPS

1. Introduction

Despite their many advantages, today's global production networks (GPN) show complex structures that are challenging to handle [1] and especially prone to unexpected disturbances [2]. The vulnerability to disruptions bears the risk of heavily disturbing the following processes, e.g., production processes. As disturbances of production and logistics processes within GPN cannot be entirely avoided, companies need to expect high additional costs, e.g., when stopping production lines. [2] Thus, production planning and scheduling (PPS) must adapt to dynamic circumstances. One way to improve flexibility and reactivity is to switch from production schedules that are fixed weeks in advance to dynamically adapting ones. [3] Such an adaptive PPS, combined with shorter reaction times to disruptions, can help mitigate the risk of part shortages, production stops, and resulting economic losses. Automated decision-making (ADM) based on traceability data offers the possibility to fulfill this goal. By localizing an object's current position, determining its status, and saving this data, traceability allows tracking the object's physical material flow and related processes. [3, 4] Thus, traceability systems create the basis for automated data usage in process control, making the most of available data. [5]

When automating a decision, manufacturing companies lack approaches that support fast implementation. Available decision-making methods like decision trees, operations research, or machine learning differ concerning required input data and the provided decision-making support. Choosing a suitable ADM method that fits a company's available data and decision requirements can be challenging, as it requires expert knowledge and profound analysis.

This paper aims to provide an ADM framework based on a previously developed traceability framework. The ADM framework guides manufacturing companies in selecting automated decision-making methods based on a specific use case they aim to improve. The approach proposed here presupposes the existence of a traceability system and is intended for use in global production networks.

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The remainder of this contribution is structured as follows: Section 2 provides a brief overview of fundamentals and state of the art concerning this paper. Section 3 outlines the concept and steps of the ADM framework. Its validation follows in section 4. Finally, section 5 discusses an evaluation, summary, and outlook of the ADM framework.

2. Fundamentals & State of the Art

The following section provides an overview of fundamentals and current research acting as a basis for the ADM framework. The framework is applicable for companies that act within *global production networks* (GPN). A GPN comprises a company's own manufacturing and distribution network and external suppliers and customers, all on a global scale. [6]

Along the supply chains within a GPN, *supply chain disruptions* can occur. A "Disruption is an unexpected event that interrupts the normal flow of goods and materials in a supply chain network and has a severe negative impact on supply chain operations and performance." [7] In case of a disruption, transparency and information exchange between actors along supply chains impact the recovery process. Thus, they are key when discussing shortening recovery times after a disruption occurs. [8]

Supply chain disruptions can affect *production planning and scheduling* (PPS) processes. Schuh & Schmidt (2014) state that PPS comprises technical order processing, from quotation processing to dispatching finished goods. Its planning and scheduling tasks work cross-functionally with the functional areas of sales. [9]

To create transparency within GPN, *traceability systems* comprise data acquisition technologies and systems managing the acquired data. [5] Transparency is crucial during disruption identification and recovery and thus acts as an enabler for process automation. [5]

Related to *decision support*, IT systems are often categorized according to their support and automation level. Bearzotti, Salomone & Chiotti (2012) divide supply chain event management (SCEM) systems into monitoring, alarming, decision support, and autonomous corrective systems. [10] Hegmanns, Parlings & Winkler (2012) introduce several categories of Logistics Assistance Systems (LAS). The target of LAS is to help companies cope with the data available in GPN by supporting planning and decision-making processes. They are usually extensions of existing systems like Supply-Chain Management (SCM) or Enterprise Resource Planning (ERP) systems. [11] The six LAS stages range from purely displaying data (stage I) to decision support (stage V) and autonomous systems (stage IV). [11]

Automated decision-making (ADM) can help with disruption management in PPS. Defining reactive measures and automating them is easy if interdependencies between PPS processes are known. An example for automating PPS controls is automated changing of formulas for calculating PPS parameters, e.g., how production priorities are calculated to decrease throughput time. [12]

There are several methods to realize automated decision-making, divided into *rule-based*, *quantitative,* and *data science* methods. *Rule-based* ADM methods include decision trees and expert systems. *Decision trees* consist of nodes and edges, starting from one root node. [13] Each node symbolizes a decision or a possible event, whereas an edge represents possible outcomes. [14] *Expert systems* perform decision-making tasks by imitating human experts' decision-making. [15] *Quantitative* ADM methods comprise operations research as well as statistics. *Operations research* works with mathematical modeling of decision problems by finding the optimal or, depending on the method, a good solution for limited given resources with the help of analytical methods. [16] *Statistics* solve real problems with the help of mathematical models in the form of distributions or processes which describe the problem appropriately. [17] The *ADM methods data science group* utilizes machine learning and data mining. *Machine learning* aims to find patterns in data with the help of mathematical methods, e.g. by structuring data. In case of insufficient or very complex data, statistical methods are applied. [18] *Data mining* refers to "[...] the study of collecting, cleaning, processing, analyzing, and gaining useful insights from data." [19]

Using real-time information, Genc (2015) introduces an *adaptive incident management approach* as part of an early warning system to make production processes less vulnerable to incidents along supply chains. [2]

Bearzotti, Salomone & Chiotti (2012)'s research introduces an approach that allows SCEM systems to autonomously steer controlling actions to decrease the impact of disruptions on currently executed plans. [10] The approach presents an *SCEM system architecture* that enables information sharing and interaction between autonomous participants along a supply chain and focuses on automating decision-making along supply chains based on traceability data. The resulting system can perform control actions autonomously in case of a disruption. [10].

The PoTracE framework introduced by Benfer et al. (2020) aims to discover the potentials of traceability. It aims to facilitate the conceptualization and implementation of traceability in industrial applications. The presented framework standardizes and accelerates the *development of traceability systems*. The structured, standardized approach, including as-is and to-be analysis and a solution toolbox, reduces the required effort for system development. The concept comprises four phases for developing, evaluating, and implementing traceability solutions: process analysis, requirement analysis, solution concept as well as the last phase, which includes implementation concept and benefit analysis. [20]

One research gap stands out when analyzing literature concerning automated decision-making based on traceability data: *The choice of an appropriate method for automating decision-making* is barely covered in the literature.

Hence, this contribution offers two new aspects: Firstly, a concept that allows the selection of an appropriate ADM method is developed, based on a traceability system, the applying manufacturing company's as-is situation, and its requirements for a future state. Secondly, the concept provides the required underlying analyses to prepare the selection and a guideline for implementing the conceptualized solution.

3. ADM framework and method selection

The ADM framework enhances the PoTracE traceability framework [20] presented in section 2 with a decision analysis, an ADM toolbox, and the required data and information basis. Thus, it applies the analysis and conceptualization methods developed as part of the traceability framework wherever suitable. In figure 1, elements taken from PoTracE are visualized in blue and grey colors, whereas the aspects specific to this paper are presented in red colors.

Implementing a traceability system can reduce the time until a supply chain disruption is detected. Based on traceability, the ADM framework aims to shorten the reaction time after the detection by automating decision-making. The framework, especially the ADM toolbox, shall act as a simple tool to help identify suitable methods for automating a decision.

The ADM framework comprises four phases described in detail in the following sub-chapters (figure 1). Phases I and II contain several steps to gather all required information for the ADM method selection, e.g. with the help of an analysis or descriptions. Phase III then selects an ADM method and phase IV finally deals with the implementation. The phases follow an iterative process. Thus, the chronological order of the executed steps is not necessarily identical to the logical order of figure 1.

3.1. Process Analysis

Starting with phase I of the ADM framework, an analysis and description of the company's *as-is state* is conducted. After this analysis, all integrated parties should have the same understanding of the considered processes to be executed when the traceability system detects a supply chain disruption. Existing workflows, possibly happening in different departments and including different stakeholders, are mapped. The stakeholders collect their pain points associated with the described processes. The phase includes a *technical analysis* including physical process and workflow analysis. In addition, an *organizational analysis* deals with stakeholder motivation, IT landscape, data management, and data requirements for as-is processes. Finally, a *decision analysis* gathers all decisions made in relation to the processes described in the technical analysis. They build a pool of potential decisions to be automated. When describing the decisions in detail, the following three key aspects should be considered:

- What does the *decision-making process* look like and which steps are necessary?
- *Who* makes the decision and which *stakeholders* are involved?
- Which *data/information* is required to make the decision?

3.2. Requirement Analysis

Phase II of the ADM framework comprises the *requirement analysis*. It aims to define a common goal for a chosen decision automation and to describe the *to-be state*. First, *application goals* based on the pain points from phase I and the company's motivation to automate decisions are defined with the help of a motivation matrix introduced by Gartner et al. (2021). [5]

The choice for one decision to be automated is made, and the ideal decision workflow and information flow are developed as part of the *application concept*. The last steps of phase II include defining *data requirements*, i.e. characterization of data and information required for decision-making, and *requirements for the decision* itself based on pre-defined criteria. *Data characterization* includes information exchange specification and criteria like data format, structure, labeling, and amount. *Decision characterization* comprises the required analytics level, assistance level, and decision influences.

Data and decision characterization are the basis for the ADM method selection process in phase III.

3.3. Solution Conceptualization and ADM Toolbox

For the solution conceptualization in phase III, PoTracE provides a traceability toolbox. As the ADM framework builds upon an existing traceability system, the toolbox is extended by an *ADM toolbox*, consisting of ADM methods and evaluation criteria. Figure 2 gives a schematic overview of the ADM toolbox components, merged in the evaluation matrix; a full list of ADM methods and selection criteria can be found in the ADM toolbox dataset published by the author. [21].

Considered *ADM methods* are *rule-based methods* (decision trees and expert systems), *quantitative methods* (operations research and statistics), and *data science methods* (machine

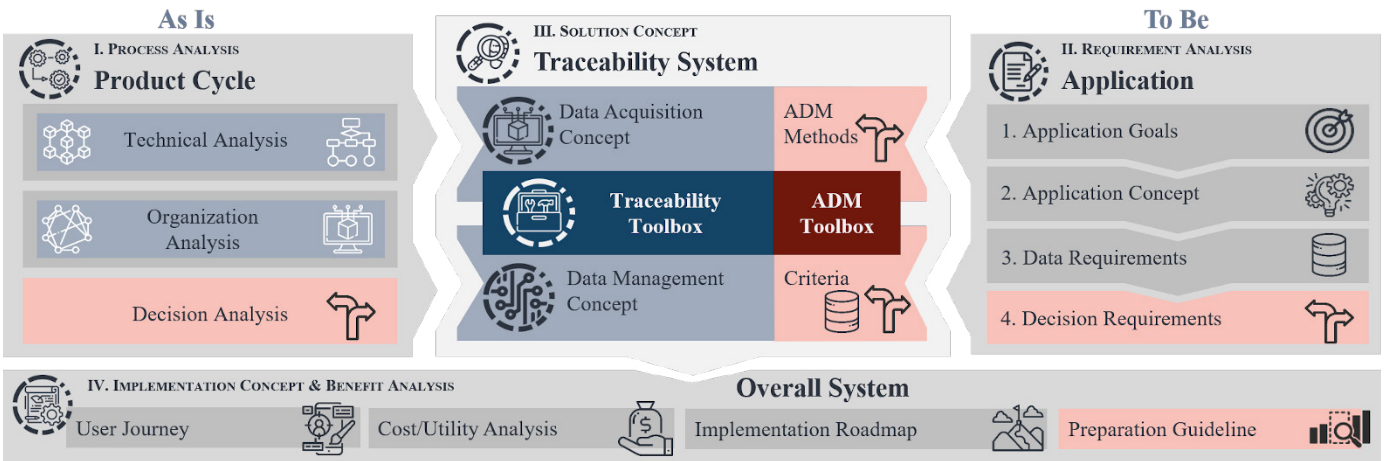

Figure 1: ADM framework based on PoTracE traceability framework

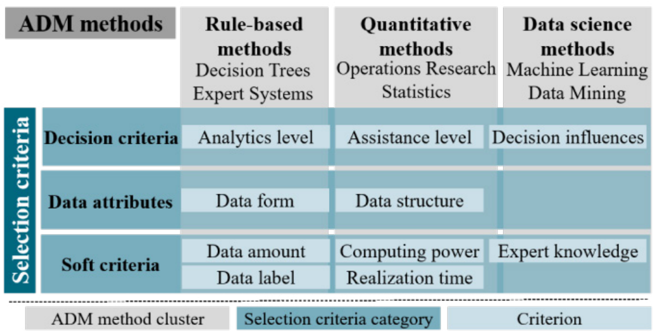

Figure 2: Schematic, high-level structure of ADM evaluation matrix

learning and data mining). The methods are clustered based on the underlying techniques they apply to find a solution for a given problem. If applicable, each method is divided into further sub-methods so that 13 sub-methods are listed and explained in the ADM method list of the toolbox.

The second toolbox component, *selection criteria*, is the basis for both data and decision characterization (phase II). Three selection criteria categories determine the structure and procedure of the ADM selection process, consisting of three stages: *decision criteria, data attributes,* and *soft criteria*.

The *ADM selection process* is the core of the ADM toolbox. Its target is to find the most suitable ADM method to automate the decision of interest. For this, the selection process uses the ADM methods and selection criteria presented in figure 2.

Figure 3 visualizes the selection process based on the criteria categories described above. Results from both phase I and II, namely decision analysis, decision, and data characterization, act as input for the ADM selection process.

As there are three selection criteria categories, the selection process is divided into *three stages*: decision criteria, data attributes, and soft criteria. Like in a funnel, each stage reduces the number of considered ADM methods gradually by matching the requirements of each criterion (defined in phase II) with the capabilities of the available ADM methods. If a method cannot fulfill the requirements, it is sorted out. The advantage of the three-stage funnel approach is that the first two stages can be carried out with the help of simple questions. This reduces the overall amount of time and effort required for choosing an ADM method, as the questions can mostly be answered based on the results of phases I and II. Only stage 3 of the selection process requires a more comprehensive decision and data analysis. However, stage 3 is only carried out if more than one ADM method remains after the first two stages. Thus, the higher evaluation effort in this stage is reduced as only a few ADM methods remain. The selection process can be stopped once only one method is left at the end of a stage. Finally, the ADM method suggested by the selection process needs to be further examined concerning its suitability for the chosen decision. If all methods are crossed out during the selection process so that none can be chosen, the input data must be adapted, or the requirements have to be adjusted to create conditions suitable for automated decision-making.

The detailed selection stages and underlying logic are described in the following.

Stage 1, *decision criteria*, concentrates on criteria concerning the decision of interest. The *analytics level* defines which method is required to achieve the chosen analytics level, whereas the *assistance level* eliminates methods that cannot serve the desired decision-making assistance. Subsequently, the knowledge and certainty level concerning the chosen decision's circumstances are evaluated with the *decision influences*. In general, all criteria values that cannot fulfill this requirement are disregarded in the further procedure.

Stage 2, *data attributes*, considers the data required to make the decision. The focus is on the data attributes from the data characterization in phase II, namely data form and structure.

The third and last stage evaluates *soft criteria*. These criteria's values cannot be determined as precisely as other criteria. For example, the required data amount is hard to quantify as it depends on the application case. Additionally, the amount of data created and processed increases every year, making it difficult to define reference values for "large" or "little" amounts of data. [22] The same applies to the soft criteria computing power and realization time. The criteria expert knowledge and data labeling are not relevant for all ADM methods and, therefore, part of the soft criteria. Criteria of the third stage are used to suggest a suitable ADM method if the criteria of the previous two stages are insufficient.

The selection process is based on an *evaluation matrix* that matches criteria values and ADM methods (figure 2). The matrix columns comprise all ADM methods and sub-methods, whereas the rows list all section criteria and respective criteria values [21]. Every sub-method and criterion value combination

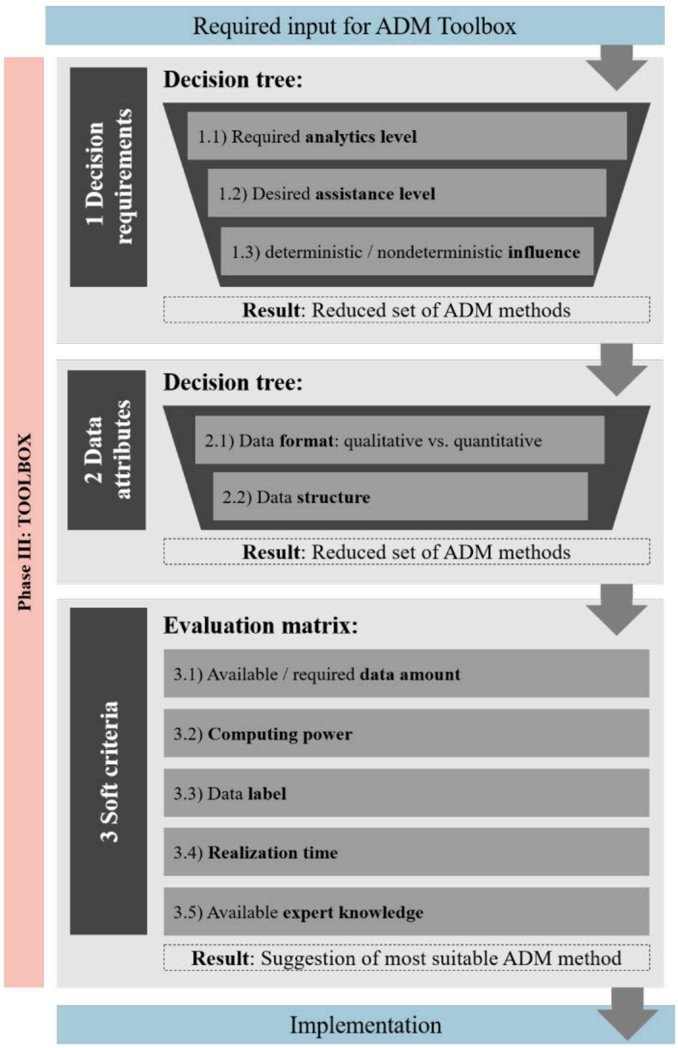

Figure 3: Three-stage ADM selection process

is assigned and evaluated based on literature research. If the method fulfills the respective requirement, the matrix field is marked with "yes", else with "no". In addition, some fields are filled with "N/A", meaning "not applicable", as either the method-criteria combination is not relevant for the scope or the criterion is not relevant for the matched method. [21]

For stages 1 and 2, a *decision tree* was derived from the evaluation matrix to simplify the process of eliminating methods that are not applicable (figure 4). For each selection criterion, it presents all possible values and assigns the ADM methods fulfilling the requirements to each, based on the matching from the evaluation matrix. For example, the criterion "data form" contains two values: "qualitative" and "quantitative". If a company needs to use qualitative data, the ADM evaluation matrix suggests to use e.g. machine learning while sorting out operations research methods, as they cannot use qualitative data [21]. Likewise, the decision tree lists the remaining ADM methods after each criterion or attribute evaluation. In case stage 3 is required, the comprised soft criteria need to be evaluated with the help of the evaluation matrix due to their special character.

Section 4 describes an application example of the selection process.

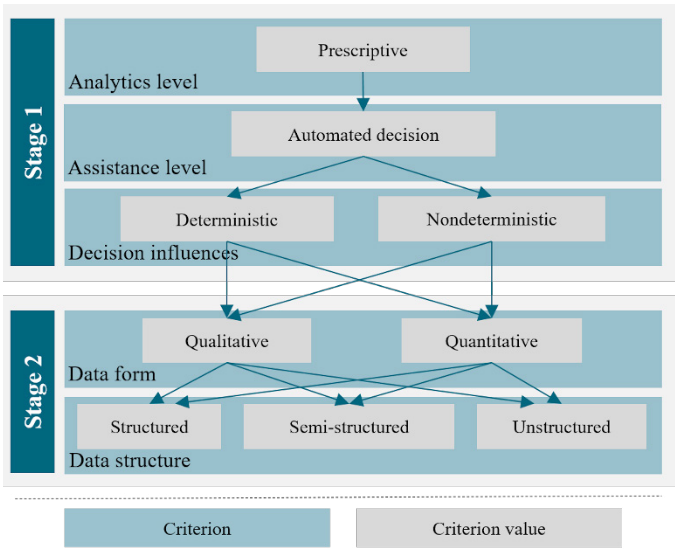

Figure 4: Schematic concept of ADM decision tree (basis: evaluation matrix)

3.4. Implementation Concept

Once an ADM method is chosen, the final phase of the ADM framework supports evaluating and preparing the implementation of the solution concept.

The PoTracE framework uses this phase to evaluate the cost and benefit related to the implementation (figure 1).

The ADM framework provides an implementation guideline to add further criteria and aspects a company should consider when implementing automated decision-making: data availability or accessibility, data quality, data reliability, and solution scalability. Additional questions are whether the chosen ADM method can be evaluated and whether a feedback loop can be implemented.

4. Validation

The ADM framework described in section 3 was validated by an exemplary use case of a globally operating truck manufacturer. After implementing a traceability system for a critical, intercontinental supply chain, an analysis showed that the manual workload was reduced, and the reaction time for the supplier management department was increased. Nevertheless, after the team had received a delay notification, the next tasks and decisions were still linked to manual and analog processes. Thus, the ADM framework was applied to one specific decision to understand whether and how the truck manufacturer could implement automated decision-making to speed up reactions to shipment delays.

Taking the process and requirements analysis results (framework phases 1 and 2, see figure 1) as inputs, a team of relevant stakeholders followed the ADM selection process as shown in figure 3.

The application scope of the framework predetermined the choice of the *analytics level* from stage 1. As the target was to automate the chosen decision, only "prescriptive analytics" could be considered. The same was valid for the choice of "automated decision" as the desired *assistance level*. The stakeholders stated that all inputs and circumstances were known for the chosen decision. Thus, the *decision influences* were "deterministic". Following the ADM decision tree and evaluation matrix (figures 2 and 4; [21]), the only ADM methods fulfilling all three criteria of stage 1 were all decision trees, all expert systems as well as linear and non-linear operations research.

At stage 2, a decision may require different data types so that more than one criterion value is chosen. In this case, the more restrictive value is used for eliminating ADM methods. For example, the truck manufacturer required qualitative and quantitative data for the example decision. As fewer methods can use qualitative than quantitative data, "qualitative data" was the more restrictive criterion value chosen for *data format*. Concerning *data structure*, the truck manufacturer plans to only use "structured data" in the future. Therefore, due to the "qualitative data" criterion value, only decision trees and expert systems remained suitable ADM methods after stage 2.

For stage 3, the truck manufacturer defined requirements based on the given soft criteria: most important were "low required computing power" and a "short realization time". Matching these values with the remaining ADM methods in the ADM evaluation matrix resulted in only one ADM method fulfilling all requirements. Thus, the ADM toolbox suggested a decision tree built from expert knowledge (not with the help of data mining) for automating the truck manufacturers' decision-making related to supply chain disruptions.

Considering the truck manufacturer's as-is situation, where structured and unstructured data in the form of e-mails were used, no ADM methods remained after stage 2. This showed that the company must make efforts to ensure conditions that allow ADM implementation.

Following the ADM framework, the next step is phase IV, implementation concept and benefit analysis, which was not conducted during the validation.

5. Summary, Outlook, and Discussion

The ADM framework supports manufacturing companies in GPN with selecting a method for automated decision-making based on the companies' requirements and available traceability data. The framework offers an ADM toolbox comprising methods suitable for automated decision-making and selection criteria. Examined methods are *decision trees, expert systems, operations research, statistics, machine learning, and data mining*. The selection criteria comprise analytics level, assistance level, and decision influences in the *decision criteria group*. *Data values* consider data form and structure. The *soft criteria* group contains e.g., data amount or realization time.

The developed framework presents methods to analyze disruption management processes, related decisions, and necessary data to provide the requirements needed to evaluate the selection criteria. Based on these requirements and the researched decision-making methods and selection criteria, a new ADM method selection process is developed. As a result, the ADM framework suggests the most suitable method to automate a specifically chosen decision, which can be taken as a starting point for implementing a *complete ADM system* capable of executing the automated decision

The ADM framework, especially the ADM toolbox, acts as a simple tool to help identify suitable methods for automating a decision. As a *generic framework*, it is not too specific or complex, so that it can be applied without too detailed expert knowledge or time-consuming analysis. However, as it refers to a rather general statement, the framework does not guarantee correctness under every possible circumstance. The models and techniques used in data mining and machine learning can be so different, that a generalized evaluation is correct for the majority, but not all techniques.

The ADM framework can be used for a gap analysis by applying the toolbox once on the as-is situation and again on the to-be situation or different scenarios. This dual-use helps to evaluate how much effort is required to make decision automation possible at the desired level.

The ADM toolbox is not specifically designed for manufacturing related decisions only. Adaption of underlying premises, like an implemented traceability system, and further development of the evaluation matrix allows general applicability. In the future, automating the ADM selection process is recommended. As this paper does not deal with the implementation of the chosen ADM method, a closer look should be taken at the technical realization as part of a complete ADM system executing the decision.

The ADM framework does not ensure data quality, which is key when making and thus also when automating decisions. The availability of consistent, correct, fully integrated data is crucial, as bad data can lead to "wrong" or misleading decisions. Additionally, the different analyses of the ADM framework do not comprise all aspects as detailed as possible. As an example, the decision to be automated should be additionally assessed, as in special cases, it might be better not to automate a decision. The ADM framework also shows a deficit concerning the analysis of a company's IT system landscape and data source integration, which can have a great impact on later implementation efforts.

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