A Prototypical Dashboard for Knowledge-Based Expert Systems used for Real-Time Anomaly Handling in Smart Manufacturing

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Abstract

The use of machine learning in digitized production increases potentials for production automation. A milestone on the path to autonomous production is real-time anomaly detection. However, increasing complexity of production makes autonomous decisions difficult to understand for humans as central stakeholders. In this paper, a dashboard is created that incorporates elements from knowledge-based systems, requirements for real-time anomaly detection, and design guidelines for dashboards. Using design science research, the dashboard is designed, implemented and comprehensively evaluated with 98 participants. After the second design science iteration, the dashboard is approved in terms of usefulness and ease of use. This research primarily contributes to practice, as the implementation constitutes a starting point for designing the interface between humans and autonomous production. The paper also contributes to academia as the dashboard is an instantiation in the research field of interface design for knowledge-based systems, which can be further developed in future research.

Keywords: Dashboard, Smart manufacturing, Real-time analytics, Expert systems.

1. Introduction

The ongoing digitalization is revolutionizing the way manufacturing companies operate (Buer et al., 2021). Worldwide, this modernization process has given rise to various terms and initiatives (Bueno et al., 2020). Leading examples are "Industrial Internet" in the USA, "Intelligent Manufacturing" in China and “Industrie 4.0” in Germany. All initiatives have in common the automation of production for the flexible fulfillment of individual customer needs. Self-x competencies are at the heart of production automation. They are implemented to transfer operational and planning responsibilities from humans to machines (Cohen & Singer, 2021). This means that production machines should be able to produce autonomously according to plan and react to changes in production programs and conditions. Self-diagnosis and self-repair competencies pursue the goal to reduce anomalies and maintain efficient, reliable production. Self-diagnosis refers to the ability to analyze real-time data for potential or existing anomalies. Self-repair capabilities aim to either prevent anomalies in an automated prescriptive manner or to eliminate them after they have occurred.

Knowledge-based expert systems (KBES) define by continuous processing and representation of knowledge. They represent a promising approach to implementing self-diagnosis and self-repair. In general, KBES are intended to support the goal-oriented and systematic application of expert knowledge (Beierle & Kern-Isberner, 2019). They can be applied in the production context to fulfill context-based, knowledge-intensive tasks, e.g. regarding anomaly diagnosis and machine repair (Leo Kumar, 2019). Expert knowledge from experience may be used to systematically eliminate anomalies or to prevent them before occurrence. An essential characteristic of KBES is that the information used and the decisions made are traceable and comprehensible at all times (Beierle & Kern-Isberner, 2019). In addition, the expansion of human-machine interaction and thus the involvement of humans in production processes is another core component of the industrial vision of the future (Kagermann et al., 2013).

However, due to flexible machine configurations, parallel sensor data streams and decision-making processes, human decision-makers face the challenge of understanding automated production processes (Schütze et al., 2018). Consequently, dashboards that take the role as human-understandable interfaces are required for KBES to depict complex production and decision-making processes in real-time. This leads to the following research question:

How can a real-time dashboard of knowledge-based expert systems used for anomaly handling in production be designed and implemented?

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The remainder of this paper structures as follows. Section 2 contains related work on dashboard design and KBES. Section 3 shows the applied design science methodology. Section 4 introduces requirements identified from literature. Section 5 covers the presentation of the implemented dashboard before it is evaluated in section 6. Finally, sections 7 and 8 present limitations and future research as well as a conclusion.

2. Related Work

This section aims to put this paper in context with state-of-the-art literature on dashboard design and expert systems for real-time anomaly detection.

2.1 Dashboard Design

Dashboards have the goal of displaying relevant information in a way that is easy to understand, so that users can obtain information about the current status of systems and processes (Eckerson, 2011). Above all, dashboards are intended to provide a basis for decision-making. For dashboard conceptualization, two essential perspectives must be considered, namely the functional and the visual perspective (Few, 2006). There are no uniform guidelines for the design of both perspectives in literature and practice. This is due to the dependency on the application domain, the addressed user group as well as the intended use of the dashboard. There are three categories that are relevant for dashboard conceptualization, namely functionality as well as scope and presentation of information (O'Donnell & David, 2000; Yigitbasioglu & Velcu, 2012).

The **functionality** of a dashboard should be aligned with the application goal. It should contain only relevant functions for information retrieval and decision support. Extended functionality beyond the intended use could lead to user irritation or distraction.

As with functionality, the **scope of information** should only include information that is appropriate to the goal. Users should receive relevant information for the fulfillment of targeted tasks, but not be overloaded or distracted by it. An inadequate amount of information can lead to wrong decisions and reduce the acceptance of the dashboard in the long-term.

The element of **presentation of information** covers the challenge of designing information in such a way that users can grasp and understand it as quickly as possible. I.e., different from scope of information, the selection from information display option is relevant. Not only the distribution of information on several pages of the dashboard is relevant, but also their arrangement. In addition, the color scheme and form of the design, such as tables or graphics, have a significant influence on the perception of the content. Above all, the way in which information is presented is contingent on context and users.

2.2 Knowledge-based expert systems for real-time anomaly detection

KBES are information systems with knowledge as their core that is used to solve a defined problem. The essential knowledge as well as its further development is stems from domain experts. By continuous knowledge representation and processing, KBES support finding domain-specific solutions. In the area of industrial production, there already are several applications of KBES (Leo Kumar, 2019). In essence, KBES should generally make or support decisions in the production process on the basis of expert knowledge. The underlying knowledge, decision-making processes and conclusions must be presented to users in a transparent and comprehensible manner.

KBES can be divided into six interrelated components (Beierle & Kern-Isberner, 2019). The authors emphasize that storage and processing of knowledge must be strictly separated from the representation of knowledge. Figure 1 shows an overview of the interrelated elements, they have been considered for the design of the prototypical dashboard.

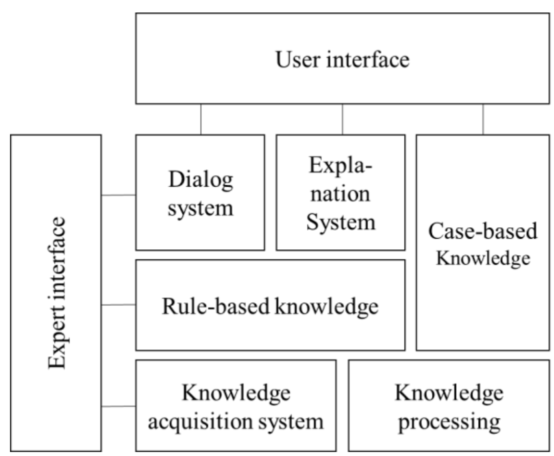

Figure 1. Generic architecture of a knowledge-based expert system (Beierle & Kern-Isberner, 2019).

Expert and **user interfaces** are used to represent or access the expert system. Both types of interfaces differ regarding the addressees and their specific tasks for which they make use of the KBES. The **dialog system** is used by both experts and users to interact with the KBES. Experts use the dialog system for development and maintenance; whereas users aim for application-oriented use. The **explanation system**

serves to explain contents and especially decisions and conclusions to the user. It has to be designed in such a way that decisions are comprehensive for every user. Knowledge directly accessible to the user is **case-based**. This means that knowledge that relates specifically to a case under consideration is stored to make currently valid facts usable. **Rule-base knowledge**, on the other hand, is only accessible to experts. Here, generally applicable rules are usually stored in the form of if-then(-else) conditions. Rules can be generic, but can also refer specifically to repetitive applications. The **knowledge acquisition** system serves for the continuous extension of the knowledge base. Ultimately, the **knowledge processing system** is internal, so experts and users can only influence it indirectly. It is used for the processing of rule-based and case-based knowledge, which takes place separately from the storage or organization of these two types of knowledge.

3. Methodology

Design and implementation of the dashboard follow a design science research approach (Peffers et al., 2007). In this approach, the dashboard as artifact that provides an answer to the research question is designed, implemented and evaluated. Figure 2 shows the phases used in the approach.

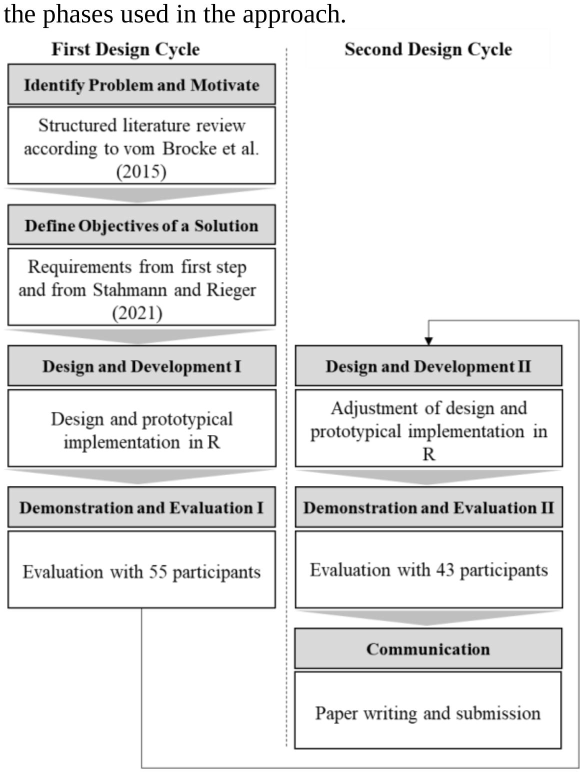

Figure 2: Design science research approach.

The motivation for the study is outlined in the first section. A structured literature review builds the basis for the motivation (Vom Brocke et al., 2015). Contributions in the databases *Google Scholar, IEEE Xplore, Scopus, Science Direct, Springer Link* and *Web of Science* were searched. These databases were chosen as they cover a variety of sources that host publications with high impact in practice and science. The following search strings were used: “expert system” AND OR(“dashboard”, “interface”, “control panel”) AND OR(“anomaly detection”, “outlier detection”, “real-time analytics”, “sensor data analysis”, “stream processing”, “streaming analytics”) AND OR(“industrie 4.0”, “industry 4.0”, “intelligent manufacturing”, “smart factory”, “smart manufacturing”, “industrial internet reference architecture”, “intelligent manufacturing system architecture”). The search terms regarding anomaly detection and industry 4.0 were added in an iterative process when encountering these terms in potentially relevant contributions. The search was not restricted to a publication date. 28 contributions resulted from scanning titles and abstracts.

In the second phase, 13 requirements identified in the literature review were used for the targeted artifact (Stahmann & Rieger, 2021). Additionally, requirements that follow from expert system conceptualization and dashboard design presented in section two were considered. The requirements also resulted from the structured literature review. In the third phase, the design science artifact was implemented in the programming language R in an iterative process with two researchers. In the fourth phase, the implemented dashboard was evaluated using a survey that contained quantitative and qualitative questions and statements. After the first evaluation with 55 participants, the artifact was adjusted. The second evaluation included 43 participants.

4. Requirements

Specific requirements were used to adapt the KBES elements from section 2.2 to real-time anomaly detection in production. Stahmann and Rieger (2021) conducted a structured literature review on requirements for real-time anomaly detection in production. The analysis of 44 relevant publications revealed 16 specific requirements in the areas data, infrastructure and analysis. The result was evaluated by means of qualitative interviews with experts from industry. Table 1 shows these requirements.

In the following, the requirements relevant to this paper will be further detailed and related to the KBES elements from section 2.2. Requirements that are irrelevant for the research purpose will be excluded explicitly.

There are five specific requirements associated with data, namely sensors, domain knowledge, historical data, simulation, and data composition. **Sensors** have become indispensable in digitized production environments as they developed from purely mechanical sensors with a specific field of application and time-delayed data transmission to internet-enabled multi-sensory devices that communicate data in real-time (Schütze et al., 2018). Sensors are seen as enablers of comprehensive real-time data analysis and presentation. They enable the acquisition of data from products, machines and entire production environments without time delay. Furthermore, literature shows the necessity that data measured by sensors should at least consist of timestamp and measured value (**data composition**).

Area	Requirement
Data	Sensors Domain knowledge Historical data Simulation Data composition
Infrastructure	Latency Reconfigurability Evaluation Notification Communication Scalability Security
Analysis	Supervised and/ or unsupervised analysis Threshold Analysis supervision Data preparation Data processing mode

Table 1. Requirements identified by Stahmann and Rieger (2021).

For KBES, sensors mean permanent data input for decision-making (Schütze et al., 2018). **Domain knowledge** as well as experience of experts are sources used for data analysis and decision making (Stahmann & Rieger, 2022). **Historical data** and analysis results can also serve as a basis for assessing anomalies in real-time. In particular, results from predictive simulations can also be used to concretize expectations of upcoming production runs and identify deviations in real production data. In KBES, these data serve to acquire knowledge that may be used as basis for rules and cases (Beierle & Kern-Isberner, 2019; Stahmann & Rieger, 2022). Furthermore, explanations for anomalies and their elimination or prevention can be given, especially by using empirical knowledge.

The area *infrastructure* includes the specific requirements latency, reconfigurability, evaluation, notification, communication, scalability and security. **Latency** refers to the time period between a measurable event and the display of the sensor data measurement (Trinks, 2018). Appropriate latency must be verifiable to ensure real-time capability. In terms of KBES, different latencies can have an impact on decisions to be made (Zalhan et al., 2020). The requirement **reconfigurability** refers to the possibility to flexibly configure machines for the production of customer-specific requirements (Berry et al., 2017). In addition, production systems must be designed in such a way that reconfiguration can be changed in the event of anomalies that cannot be directly prevented or eliminated. For KBES, this means that knowledge for diverse possible machine configurations shall be available for decision-making. In addition, the explanation system should also be able to guarantee traceability (Beierle & Kern-Isberner, 2019). **Evaluation** refers to the permanent assessment of data streams to determine whether anomalies are present and, if so, how serious they are (Berry et al., 2017). For this purpose, algorithms can be used that provide real-time indications as to whether values correspond to expectations. Analysis results and decisions should be presented to users in production as **notifications** (Han et al., 2018). Literature shows the use of alarms or text messages directed to employees that are affected by potential anomalies. **Communication** is the basic requirement of a dashboard through the adequate presentation of relevant information as explained in chapter 2.1 (Carvajal Soto et al., 2019). Accordingly, each element of the dashboard to be created serves to fulfill the requirements for communication. **Scalability** and **security** are not considered in detail in this paper, as they are not directly related to KBES components and therefore do not appear in the dashboard to be developed.

The last area refers to requirements for the analysis of data streams in real-time. The identifiable requirements are data preparation, data processing mode, analysis methodology, thresholds and analysis supervision. The analysis methodology refers to the type of algorithmic data analysis used for anomaly detection. Unlike **unsupervised algorithms, supervised algorithms** require training data and learning phases. Type and functionality of algorithms can affect decision-making capabilities in KBES (Lavin & Ahmad, 2015). **Thresholds** are upper and lower limits of the data. If data exceed these limits, they are always considered anomalies. In their qualitative survey, Stahmann and Rieger (2022) identified thresholds as one of the most important means to detect anomalies in practice. Threshold values are set based on expert knowledge, historical data, or simulations. In KBES, they can be used to design rules and cases (Beierle & Kern-Isberner, 2019). Similar to the communication requirement, the dashboard is generally used for **analysis supervision**, as detailed in chapter two. **Data preparation** and **data processing mode** are not requirements that are implemented as part of the design of a dashboard for KBES for anomaly handling.

5. Dashboard Design

For the dashboard design, the elements of KBES (cf. Figure 1), the requirements from literature (cf. Table 1) and the dashboard design elements (cf. Section 2.1) were considered. In addition, the guidelines of DIN 9241 were taken into account. The dashboard was designed in an iterative process with two researchers. The implementation can be accessed openly at: https://bit.ly/391oZkb.

The dashboard consists of three pages with the titles “Overview”, “Sensors” and “Rules/Cases”. The presentation is based on a fictional production scenario, which was created iteratively in correspondence with two practitioners with three and eight years of experience in production. In the fictional scenario, four sensors are attached to three CPS. The assignment of the design elements (DEs) to the KBES is detailed in the evaluation chapter. Figure 3 shows the “Overview” page, which consists of four DEs. DEs 1.1 and 1.2 show graphs that give a first visual impression of the current sensor data and the currently present anomalies with respect to a categorization of their criticality. The categorization is done from historical data, expert knowledge and previous simulation (Stahmann & Rieger, 2022). The two DEs meet the infrastructural requirements of real-time notification and evaluation on anomalies. The latency requirement is also met, so that the user can assess adherence to real-time requirements. Additionally, the DEs meet the requirement of analysis supervision due to the availability of analysis results and progress. DE 1.3 presents a table that allows detailed insights into the anomalies. In addition to ID and time, the table contains information on criticality and the reason for the anomaly. Furthermore, there is a column for specifying the automated solution attempts using rule-based or case-based knowledge. Another column details whether the automated solution attempt was successful, i.e. whether the anomaly could be eliminated before or after occurrence. Users and experts have the opportunity to comment each line. DE 1.3 compensates the visual information from DEs 1.1 and 1.2. Consequently, the requirements of real-time notification, evaluation and analysis supervision are addressed. DE 1.3 also considers the requirement to take into account historical data. In addition, DE 1.4 is a button to download all current and historical data as CSV file.

Figure 3: Page "Overview" incl. demarcation of DEs.

Figure 4: Page "Sensors" incl. demarcation of DEs.

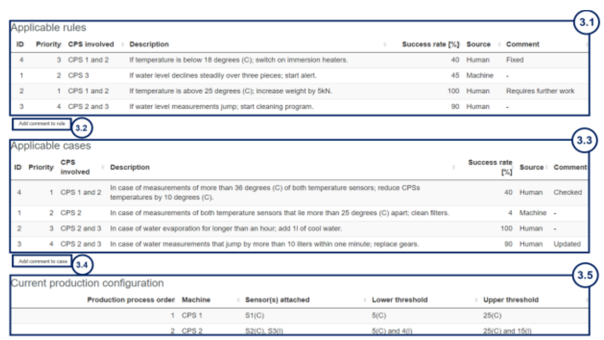

Figure 5: Page "Rules/Cases" incl. demarcation of DEs.

Figure 4 shows the page “Sensors”, which is used to display anomalies and information for algorithmic real-time data analysis per sensor. The page consists of six DEs. DEs 2.1 and 2.2 are dropdown menus that allow the selection of sensors and anomaly detection algorithms as different algorithms output different anomaly detection results (Wolpert & Macready, 1997). They address the requirement to differentiate data per sensor and analysis results per supervised or unsupervised anomaly detection algorithm. DE 2.3 extends the implementation of the latter requirement and shows metrics for evaluating the algorithms per sensor. DEs 2.4 and 2.6 represent content per sensor and algorithm. For each sensor and algorithm combination, the DEs address the same requirements as DEs 1.1 and 1.3. DE 2.5 shows according to the selection how many anomalies were tolerated, prevented and solved. Thus, DE 2.5 meets analysis evaluation and supervision requirements.

Figure 5 shows the "Rules/Cases" page, which consists of three tables. The first two tables (DEs 3.1 and 3.3) detail applicable rules and cases and thus represent the knowledge base. The tables show prioritization, involved CPSs and a description of the rules and cases. The table also indicates the success rate of rules and cases as well as currently valid thresholds for sensor measurements. Furthermore, the source from which the rule or case was originally proposed is mentioned. Finally, there is also the possibility for experts to comment lines via buttons (DEs 3.2 and 3.4). The DEs therefore meet the requirements of domain knowledge integration and threshold clarification. DE 3.5 gives an overview of the currently valid configuration, i.e. CPS and sensors are put into relation to address the corresponding infrastructural requirement. Additionally, all elements of all three pages have explanations of the elements in mouseover tooltips.

6. Demonstration and evaluation

The implemented dashboard was demonstrated and evaluated using a survey. Participants were acquired in university courses that relate to decision support systems, information systems and business administration. Students were essentially chosen as participants because, as digital natives, they are considered tech-savvy (Hernandez-de-Menendez et al., 2020). As potential future users of KBES dashboards in production, students are a key stakeholder group. Additionally, practitioners from the fields of production were invited via e-mail. In the first iteration, there were 55 participants, among these were 50 students, eight of them had relevant practical experience in production. From the five practitioners, four worked in production and one in software development and evaluation. In the second iteration, there were 43 student participants, among these six had relevant practical experience.

The survey was created and revised in an iterative process with overall three researchers. It consisted of four pages, where each page covered questions for one dashboard page. Additionally, there was one page of socio-demographic questions. The survey contained 32 quantitative statements. The statements orient towards the dimensions perceived usefulness and perceived ease of use from the technology acceptance model (Venkatesh & Bala, 2008). The former refers to the support of job relevant activities by the artifact, i.e. anomaly detection, elimination and prevention. Perceived ease of use refers to the effort required to use the artifact for job relevant activities. The participants had to assess these statements using five-point Likert scales, ranging from 1 "strongly disagree" to 5 "strongly agree". An odd number of choices was given on the Likert scale to make a neutral stance possible (option 3: "neutral") and did not enforce a tendency. Additionally, eleven open questions aimed at yielding qualitative feedback on the dashboard's pages. The evaluation of most dashboard elements based on the assessment of multiple related statements or open questions to ensure reliability (Bell et al., 2019).

KBES element	**DE**	**Eval. II**	
		Mean	**Var.**
Dialog system	1.3	3.94	2.48
	2.1	4.39	0.52
	2.2	4.07	0.78
	2.6	4.04	0.61
	3.2	3.86	0.55
	3.4	3.98	0.93
Explanation system	1.1	3.56	0.66
	1.2	3.89	0.85
	2.4	4.11	0.88
	2.5	3.99	0.79
Explanation system, knowledge acquisition system	2.3	3.88	0.68
Explanation system, rule-based knowledge	3.1, 3.5	4.01	0.73
Case-based knowledge	3.3	4.19	0.96
Overall		**3.99**	**0.88**

Table 2: Evaluations for statements on functionality.

The survey was conducted in German and later translated to English as all participants were native Germans. It was pretested with four students and two practitioners from production.

Table 2 shows the aggregated evaluations used to assess functionality of the DEs of the implemented dashboard from the second evaluation iteration. All statements are presented in relation to the dashboard elements and the requirements from literature. An exemplary statement for the evaluation of functionality is “The table is useful for real-time monitoring of anomalies.”. All in all, the statements on functionality were given an average rating of 3.99 ("I agree"). The average variance is 0.88. Dialog system and explanation system cover the most DEs. Both were rated on average with 4.05 and 3.89 respectively. The combination of explanation system and rule-based knowledge in DEs 3.1 and 3.5 and the case-based knowledge in DE 3.3 received an average rating of 4.01 and 4.19. Yet, in qualitative questions, the participants argued for a clearer visualization on the “Rules/Cases” page. Participants specifically asked for a presentation of thresholds that should be more easily recognizable.

Table 3 covers the second iteration’s evaluation results concerning scope of information. An exemplary statement regarding the facilitation to use the dashboard is “The mouseover text for table and graphs is helpful for using the dashboard.”. Statements relating to the scope of information refer to the two interface components and the dialog and explanation systems. User interface and expert interface are not combined in the results for scope and presentation of information. Overall, an average of 3.99 ("I agree") is achieved. The variance is 1. In line with suggestions from qualitative answers, the third page "Rules/Cases" receives the lowest average rating. Regarding scope of information, qualitative results for this page refer to the fact that the information given is difficult to put into the context of the information on the other two pages.

KBES element	DE	Eval. II	
		Mean	Var.
User interface, expert interface	1	4.46	0.52
	2	4.5	0.44
	3	3.14	2.12
Explanation system	3.5	3.86	0.93
Overall		3.99	1

Table 3: Evaluations for statements on scope of information.

Table 4 shows the second iteration’s evaluation of the presentation of information, an exemplary statement is “Overall, I find the Overview page visually appealing.“. For the element presentation of information, an average result of 3.84 ("I agree") was achieved with a variance of 0.79. The best result was achieved by the page "Sensors", the worst again by the page "Rules/Cases".

KBES element	DE	Eval. II	
		Mean	Var.
User interface, expert interface	1	3.89	0.81
	2	3.96	0.6
	3	3.66	0.96
Overall		3.84	0.79

Table 4: Evaluations for statements on presentation of information.

Table 5 shows the qualitative feedback aggregated for both evaluation iterations. Qualitative feedback was aggregated by one researcher in a process of two independent iterations. process Suggestions from the first iteration could essentially be implemented, so that they no longer occurred in the second iteration. One exception was the request for clearer visual demarcation of objects. Furthermore, the participants wished for possibilities to individualize the dashboard according to their needs. On the one hand, the user should be able to resize the objects of the pages as required. On the other hand, the columns of the tables should be selectable by the user for better clarity. These suggestions are starting points for future research.

Cycle		Qualitative Feedback
I	II	
X		Clearer assignment of sensors and machines.
X	X	Clearer visual demarcation of objects.
X		Clearer visualization of thresholds.
X		Different arrangement of objects.
X		Different color design of tables.
X		Export option for historicized data.
	X	Option to resize objects individually
	X	Option to select table columns individually
	X	Point out origin of rules and cases

Table 5: Qualitative feedback from both evaluation iterations.

7. Limitations and Future Research

Although the design of the prototypical dashboard was derived multicriterially, its implementation is still subject to the interpretation of the researcher. Yet, the iterative implementation with two researchers, pretests as well as the positive evaluations from students and practitioners support the successful development of the prototypical dashboard.

The participants from the two evaluation cycles are mainly students, but also practitioners took part. All participants are from German-speaking countries. Future research can expand the evaluation by using a heterogeneous group of participants. This heterogeneity may reduce e.g. cultural bias and position bias in the evaluation.

While the data from the study was validated with experts, the data is still fictional. Future approaches may use real data to represent a real scenario. However, also in the case of real data, dashboards need to be customized to any specific use case to ensure specific decision support. For this purpose, the dashboard represents an evaluated prototype as basis for individualization.

For future improvement, the design science approach can be continued with a third cycle. Potential for improvement is provided by both the quantitative and qualitative points from the evaluation.

8. Conclusion

The digitization of production enables machines to make autonomous decisions during production processes. A key component in promoting machine autonomy is the automated detection of anomalies in real-time. However, automated decision-making processes, especially in real-time, are difficult to understand for humans as key stakeholders of production. This research contributes to the handling of anomalies in production with a prototypical design and implementation of a real-time dashboard. The goal was achieved using design science research methodology. The dashboard elements were derived using multiple criteria. Requirements from literature and components of knowledge-based systems were used for the structural and content-related design of the dashboard. In addition, the criteria scope of information, functionality and presentation of information, which were identified in the literature, were also considered for dashboard design. The visual design was supported by adherence to DIN 9241.

Each element of the dashboard was successfully evaluated in two cycles with a total of 98 participants from academia and practice. Furthermore, as a result of the evaluations, starting points for the further development and individualization of the prototypical dashboard were identified.

This research contributes to both practice and academia. The contribution goes into the field of the design of the interface between humans and autonomous production. Practitioners can use the prototypical implementation as a basis for customization to their own specific requirements. The results of the evaluation provide starting points for own improvements. The prototypical dashboard also serves as a contribution to the research field of interface design for KBES. The research contribution can be expanded by continuing the design science cycles and by further evaluations.

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