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Framework For Context-Sensitive Dashboards Enabling Decision Support On Production Shop Floor

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Abstract

The advancing digitalization of production means that a large amount of data and information is being collected. Used correctly, these represent a significant competitive advantage. Decision support systems (DSS) can help to provide employees with the right information at the right time. Context-sensitive dashboards in the sense of decision support have the potential to provide employees on the shop floor with information according to their needs. Within the scope of this work, a framework for the determination of the context-sensitive information needs of the staff on the shop floor was developed. The goal was to reduce the development and adaptation effort of a context-sensitive application by classifying activities with similar information needs in advance. According to the methodology, the information needs of the employees are first analyzed and activities are summarized in terms of their general information needs. Subsequently, information needs are weighted in order to prioritize them with regard to the processing and selection of information. The context-sensitive dashboard was implemented using a user-centric approach to achieve a high level of user acceptance. Finally, the developed prototype, including architecture and design, was tested and evaluated by experts. Three scenarios were compared in which experts were asked to assess the information requirements for employees in production. These results were compared with the results of the framework. The comparison showed that for two of the three scenarios, the weighting determined in the framework matched the experts' assessments to a high degree. These general scenarios show that it is possible to generate context-sensitive dashboards based on demand using the developed framework. If the activities become more specific, it became apparent that further developments of the framework are necessary to cover the corresponding information needs. For this purpose, an iterative application to further scenarios and subsequent implementation in the framework seems to be purposeful.

Keywords

Context-Sensitive; Decision Support; Dashboard; Production Shop Floor; Framework

1. Introduction

The advancing digitalization of production means that a large amount of data and information is being collected. Used properly, these represent a significant competitive advantage. Decision support systems (DSS) can help to provide employees with the right information at the right time. Context-sensitive dashboards in the sense of decision support have the potential to provide employees on the shop floor with information according to their needs.

First, we will discuss current developments for support on the production shopfloor. Based on this, we propose a framework that was developed for determining the context-sensitive information needs of staff on

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the shop floor. The goal was to reduce the development and adaptation effort of a context-sensitive application by pre-classifying activities with similar information needs. According to the methodology, the information needs of the employees are first analyzed and activities are summarized in terms of their general information needs. Subsequently, the information needs are weighted to prioritize them with regard to the processing and selection of information. Afterwards, the context-sensitive dashboard was implemented using a user-centric approach to achieve a high level of user acceptance. Finally, the developed prototype, including architecture and design, was tested and evaluated by experts, validating the framework and concluding this paper.

2. Recent Developments for Support on Production Shop Floor

2.1 Decision Support Systems

In a modern production environment, people, machines and products are networked via the internet and exchange information with each other. This is where DSS come in. Because the increased flexibility and dynamics in production mean that production processes need to be adaptable, DSS can enable that the right information is available to operators at the right time and in the right place. [1]

The aim of such systems is to enable decision-makers to make decisions of the highest possible quality by collecting, processing, analyzing and providing information and data. To this end, large volumes of data can be processed automatically and visualized clearly for the user. Frequently, DSS do not offer the user just one solution, but compare several alternatives with regard to their advantages and disadvantages. [2] The advantage of an DSS that integrates humans into the decision-making process is particularly apparent in the presence of uncertainty and when no clear patterns in decision-making are apparent. In this case, human intelligence is superior to computers. [3]

Common DSS used in almost every modern production facility include Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) systems. With the help of Manufacturing Execution Systems (MES), production processes can be planned and controlled and the material and information flow of production can be mapped. In contrast to MES, enterprise resource planning (ERP) systems operate at a lower level of detail over the medium and longer term. These systems are used to manage operational resources such as production equipment, personnel and capital. [4–6]

Both ERP and MES are limited in their flexibility and data-driven process optimization for direct use as DSS on the shop floor [7]. For this reason, there are many different DSS designed to support specific activities and processes on the shop floor. Through smaller and more powerful devices connected via the Internet, ergonomics and the number of integrated functionalities is increasing.

2.2 Dashbords

On the shop floor, DSS are often used in conjunction with dashboards. These are divided into three different types: strategic, tactical and operational. Strategic dashboards can be used to monitor the company's progress towards strategic goals, whereas tactical dashboards are used to monitor progress and trends for all of an organization's strategic initiatives. Because this work focuses on operational dashboards they will be explained in more detail. Operational dashboards are dashboards used to monitor enterprise processes, activities, and complex events. Generally, the user interface provides daily or weekly updates or near real-time charts and reports that illustrate the status of business and production processes. By using dashboards on a regular basis, problems can be identified early and actions can be taken. Because of their practical nature, they are not used at higher levels of the organization, but where the processes and activities take place. Like tactical dashboards, the narrow scope of operational dashboards requires detailed information with strong analytical capabilities. In light of a dashboard's limited screen space and high level of specialization, operational dashboards in particular must be tailored to the needs of their target users. [8,7,9]

2.3 Context-Sensitive Systems

The generally accepted definition of context by DEY [10] is extended by ROSENBERGER et al. [11] to improve its applicability with respect to the industrial domain. The term context refers to any information that can be used to characterize an entity, its state, or its environmental situation, if the information is considered relevant for the interaction between user and application. An entity can be a person, a place, or a tangible object or intangible state, including the user and the application itself. [12,13] Context-sensitive systems are rarely used in industrial applications. Due to the increasing proliferation of mobile devices and wearables, systems with location recognition are increasingly used. [14,15] According to ALEXOPOULOUS et al. [16], successful architectures for context-aware applications in production should have the following common characteristics:

1. multi-tier architectural approach that encapsulates features and functionalities.
2. event-driven approach, due to the multiplicity of IoT-enabled devices
3. context sensitivity should be supported by technologies such as ontologies and semantics.

ROSENBERGER et al. [11] developed a process model for the development of context-sensitive systems for industrial applications. A cross-phase user-centered approach for context determination is presented, which combines tasks of the process definition and context determination phases. This is used as an orientation for later implementation in this thesis. A comprehensive overview of the use and research status of context-sensitive systems can be found in PERERA et al. and HONG et al. [17,18].

3. Framework for Development of Context-Sensitive Dashboards

ROSENBERGER et al. propose a general process model to develop context-sensitive systems [11]. It divides the analysis and design phase of context-aware systems into three stages:

1. Activity determination: identification of activities to be supported by context-aware functionalities.
2. Process definition: Determination of how the system should react to the occurrence of a context.
3. Context determination

Based on the general procedure for the development of context-sensitive systems presented above, a suitable procedure for this work is developed below. One of the main reasons for the high development effort of context-sensitive applications according to the framework from ROSENBERGER et al. is the individual consideration of individual activities. As described, production scenarios on the shop floor are becoming more dynamic, complex and subject to constant adaptation. On the one hand, this means that an increasing number of activities must be considered and analyzed individually. On the other hand, the increasing dynamics of production means that new activities occur that were not taken into account during the development of the original application. To update the application, the entire process model must be run through for the new activities.

A major goal of this work is to reduce the effort required to create a context-sensitive application and thereby increase the benefit-to-expense ratio. To achieve this goal, a new process model is developed, shown in Figure 1. This model takes the approach of reducing the number of activities to be analyzed by grouping individual activities into classes that have the greatest possible degree of overlap in terms of system response and contexts.

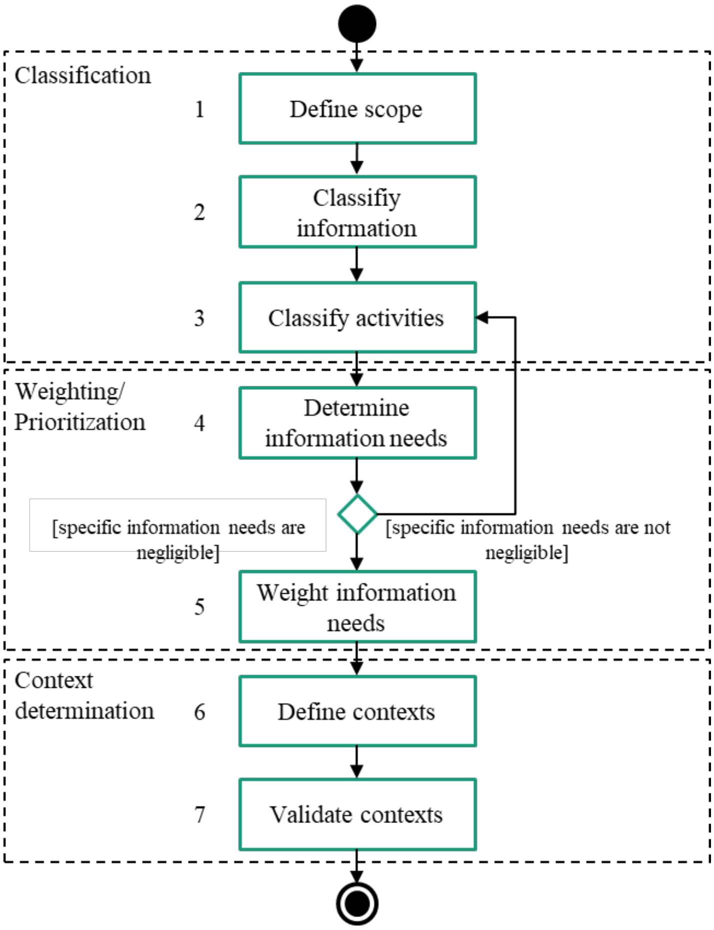


Figure 1: Framework for developing context-sensitive dashboards

After the definition of the scope (step 1), the information that is of interest to the shop floor personnel is classified (step 2). Subsequently, the activities occurring within the definition area are identified. These activities are analyzed and classified (step 3) with regard to their system response. In the case of the DSS acting passively here, the system response corresponds to the change in the displayed information or the information requirement of the personnel for the execution of the activity. In the following step, it is checked whether the selected classification is suitable for further development (step 4). This is the case if the intersection of the common information needs of the respective class is sufficiently large or the share of the activity-specific information needs is negligibly small. If this criterion is not met, the classification approach must be adjusted (step 3). This is followed by the weighting or prioritization of the relevance of the information needs (step 5). Relevance in this context means the significance of the information requirement for the shop floor personnel. On the one hand, the effect or the influence of the information, on the other hand, the probability of occurrence of the information need in dependence on the specific activity is considered. Finally, the contexts are assigned to the activity classes based on categories and validated (step 6 and 7).

4. Applying the Framework to the Production Shop Floor

After presenting the general framework for the development of context-sensitve dashboards, it will now be operationalized to the production shop floor. For this, the steps referenced in Figure 2, which need operationalization will be described in detail. In the case of appliyng the framework to the shop floor the infromation needs from step 4 coincide with the classified information from step 2. The steps 4 and 7 (determine information needs / validate contexts) are therefore excluded from the next subchapters.

4.1 Definition of Scope

As shown in Figure 1, the first step is the definition of scope. The production shop floor will be the frame of reference for the application of the framework. In the following subchapters, a distinction is made between the direct areas (fabrication and assembly) and the indirect areas (logistics, maintenance and quality assurance). Also, production planning and control will be included as a separate area. Shop floor personnel refers to all persons who perform activities in these areas.

According to the classification of dashboards described earlier, this work reffers to an operational dashboard. In this context, it is a passive DSS that clearly provides information for process monitoring and control. The individual needs of the user are to be fulfilled by real-time information to enable faster and high-quality decision-making.

4.2 Classification of Information

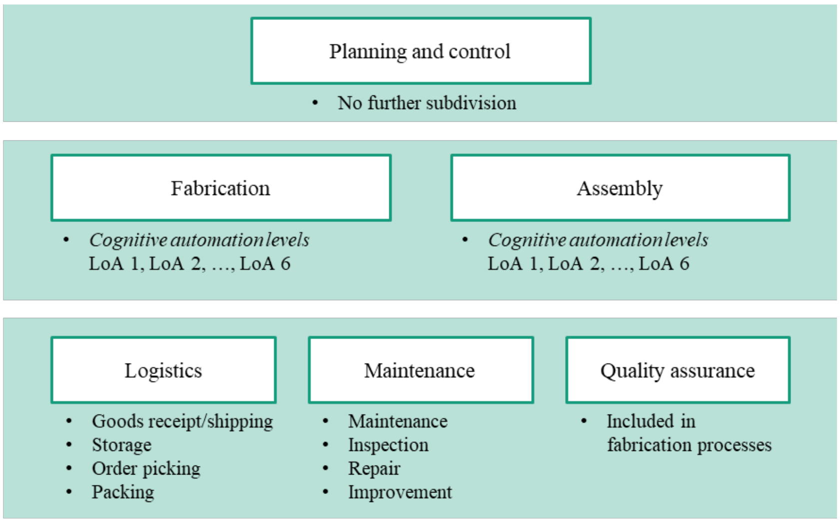
The second step according to the framework is the classification of information. As shown in Table 1, the general categories for information needs (context, performance, knowledge and communication) can be subdivided into more specific categories. Specific information from MES, ERP, and other data sources can be assigned to these categories in the implementation of the DSS.

Table 1: Classification of information needs on the shop floor adapted from [19]

General information needs	#	Specific information needs
Context	1	Alarms, warnings, notices
	2	Order information
	3	Information about completed/planned orders
	4	Information about previous/future process steps
	5	Environment information
	6	Contact information of responsible persons
Performance	7	Company related KPI
	8	Production line related KPI
	9	Process-related KPI
	10	Personnel-related KPI
Knowledge	11	Detailed, interactive work steps/instructions
	12	Safety/health instructions
	13	Resource information
	14	Process improvement
	15	Documentation
Communication	16	synchronous
	17	asynchronous

4.3 Classification of Activities

In the following, the various areas of the shop floor are examined in more detail and a suitable classification approach is sought for all the activities occurring there (cf. step 3 in Figure 1). For each of the six different areas, a classification approach is identified that can be used to group the activities into subcategories. These subcategories should be selected in such a way that they have as large an intersection as possible in terms of their information requirements, or that the amount of activity-specific information is negligibly small. Figure 2 shows an overview of the different activities on the shop floor and their respective classification approach.



LoA: Level of Automation

Figure 2: Classification of shop floor activities

A suitable classification approach for fabrication and assembly activities can be the classification by different degrees of automation after [20]. The Level of Automation (LoA) within production is defined as the division of physical and cognitive tasks between humans and technology into a spectrum ranging from fully manual to fully automated. Each of these tasks can then be classified into seven levels, from fully manual control to fully automated. Both the degree of physical and cognitive assistance can thus be assessed on a common scale. In general, the need for information for shop floor personnel decreases with higher levels of automation. For the other shop floor activities, the classification can be seen in Figure 2.

4.4 Weighting of information needs

To enable the system to process and select which information is to be displayed prioritized in the specific case, a weighting of the various information needs is carried out for this purpose (cf. step 5 Figure 1). For each specific information need (criterion), a weighting factor (weight) w_j is determined. This factor is usually set up to be between 0 and 1 on a cardinal scale.

$$\sum_{j=1}^{n} w_j = 1 \tag{1}$$

n = number of criteria

The weights can take on different functions, depending on the decision procedure. In this paper, the most common interpretation of the weighting factor is the relative importance of one criterion over the others. Since these weights are assigned subjectively, it is important to show the decision process towards them as transparently as possible. One goal is therefore to ensure that the weighting made is comprehensible and, can be adjusted without great effort. [21]

Many methods for determining the weights can be found in the literature. The procedure used here is based on the Failure Mode and Effects Analysis (FMEA) [22,23]. Based on this methodology, the effect of specific information requirements on the shop floor is estimated. To make this assessment and weighting more consistent and comprehensible, the following four fundamental criteria are introduced:

1. Occupational safety
2. Product Quality
3. Adherence to delivery dates
4. Productivity

These fundamental criteria cover the key risks on the shop floor and are weighted relative to each other. The calculation of the weight g_i of the respective specific information requirement results as follows:

$$g_i = \sum_{j=1}^{n} k_j * x_j \tag{2}$$

n = number of fundamental criteria

k_j = weight of the fundamental criterion

x_j = importance of error effect

Regarding the importance of the error effect x_j, weights from 1 (no impairment) to 10 (dangerous/illegal) are assigned. In the context of information needs, this weighting signifies how relevant specific information is to avoid errors or complying with the fundamental criteria. The probability of occurrence plays a role in the subsequent step, which is determined for the various defined activity classes of the respective specific information needs. This is done in the form of an argumentative approach, which enables a general estimation of the frequencies or probability of occurrence (equivalent to FMEA) of the information requirement. Since this assignment is carried out at a rather high level of abstraction and subjectively, a deficit of the classification approach arises at this point. For this reason, the weighting was designed in such a way that it is also possible to change certain weighting parameters retrospectively and to adapt them individually to the shop floor. In addition, due to the high degree of abstraction, specific activities may have information needs that deviate from their class, which cannot be covered by the classification scheme. To compensate for this deficit, a personalization function can be provided in the later application. Finally, the weights of the specific information needs are determined based on the effect of the information needs and the occurrence probabilities. Here, the weight of the specific information need is $w_{i,j}$:

$$w_{i,j} = g_i + P(I)_{i,j} * \frac{1}{\sum_{i=1}^{n} g_i * P(I)_{i,j}} \tag{3}$$

g_i = effect of the information need

$P(I)_{i,j}$ = probability of occurrence of the specific information need

Index i refers to the class of information need (e.g., order information, information about completed/scheduled orders, etc.), index j refers to the activity class (e.g., LoA 1, LoA 2, etc.). The second part of the formula includes the normalization of the absolute values, which results in the sum of all weights corresponding to an activity class 1.

4.5 Definition of Context

In this paper, the scheme of ROSENBERGER et al. is used, to classify context [11]. To better represent the industrial environment, the core categories *user, environment and system* are extended in this case by the specific categories information retrieval and pattern recognition. The relevant contexts for this work are depicted in Figure 3.

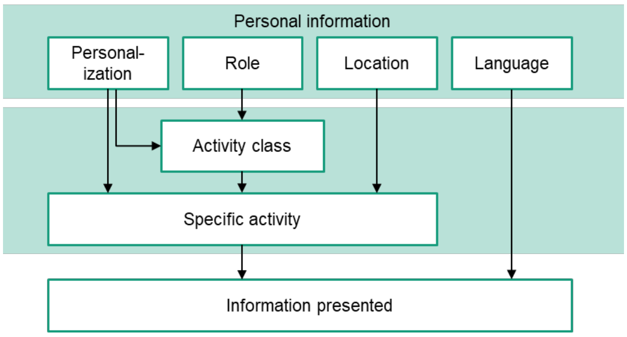


Figure 3: Context model for shop floor personnel

5. Prototype and Validation

With the developed framework, the specific information needs and weights were assessed. Additionally, a prototype dashboard was developed, using the underlying assumptions. For the validation, three different exemplary scenarios were considered in which experts for production assessed the information requirements. For this purpose, the various available information was to be sorted into a ranking order with regard to its relevance for the specific scenario. In each case, 17 application-specific pieces of information were listed for each scenario, which were to be ranked in terms of their relevance for the activity to be performed (prioritization from 1 to 17): 1 Information on dimensions and tolerances of the workpiece; 2 Information about follow-up order; 3 Information about previous production steps of the workpiece; 4 Note: Check filling level of cooling liquid; 5 Humidity of the environment; 6 Contact information of the person(s) responsible for the machine; 7 Averaged scrap rate of the entire production; 8 Overall equipment effectiveness OEE; 9 Average cycle time of the process; 10 Personnel-related number of completed production orders; 11 Detailed work instructions for the production of the workpiece; 12 Safety instructions: Wear safety goggles and gloves; 13 Set speed of the milling head; 14 Suggestion for process improvement: Second step of the instructions is misleading; 15 User manual of the milling machine; 16 Real-time support via video chat with production manager; 17 Text message from production manager about machine inspection the following day. Subsequently, this assessment was averaged and compared with the determined weights (see Figure 4).

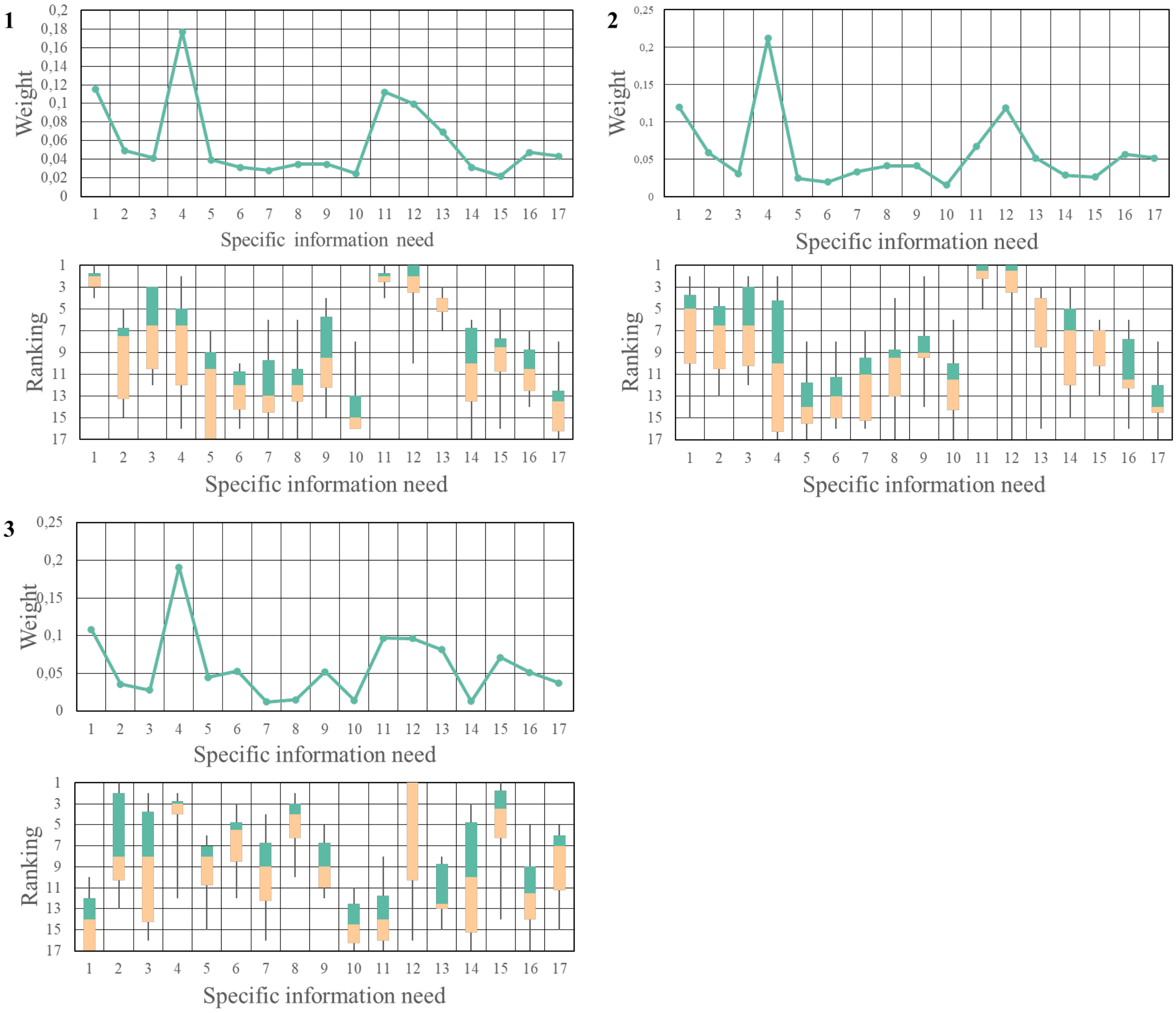


Figure 4: 1: Validation results for scenario 1,2 and 3 (corresponding bold numbers), model output for weighted infromation needs on top, results from expert questionaire on the bottom (boxplots, number of participants n = 8)

Scenario 1 involves a manufacturing activity on a milling machine in which no automation technology has been installed. Thus, the technology does not challenge the execution of the user's actions, nor does it take over parts of the control of the process (LoA 3). In Scenario 2, the milling machine has been upgraded and now has sensor and control technology that allows the process to be checked and corrected (LoA 6). In the third scenario, a maintenance activity is performed on the milling machine.

The comparison of the results of the first two scenarios has shown that the weighting of the framework and the assessment of the production experts coincide to a high degree. Only a few specific information requirements differ significantly. This raises the question of whether the experts' assessment produces better results than the argumentative approach.

The consideration of a maintenance activity has shown the limitations of the framework. Once activities become too specific, the generalized classification approach followed in the paper cannot cover all specific information needs. However, this shortcoming could be compensated by a personalization feature and iterative improvement through user feedback in the later application.

6. Conclusion and Outlook

This paper proposed a framework for the development of context-sensitive dashboards. It has been implemented as a prototype and validated through expert interviews. The comparison showed that for two of the three scenarios, the weighting determined in the framework matched the experts' assessments to a high degree. It must be said though, that the number of experts for validation was very limited (eight). By increasing the audience for validating the framework, the results shold be further analyzed. These general scenarios show that it is possible to generate context-sensitive dashboards based on demand using the developed framework. If the activities become more specific, it became apparent that further developments of the framework are necessary to cover the corresponding information needs. For this purpose, an iterative application to further scenarios and subsequent implementation in the framework seems to be purposeful.

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Biography

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