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Success Factors for the Validation of Requirements for New Product Generations – A Case Study on Using Field Gathered Data

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Abstract

This paper investigates which activities and success factors can be identified for the data-driven validation of functional requirements. For this purpose, a case study is conducted at a machine tool manufacturer. To validate functional requirements by analyzing data of reference products, these activities must be performed iteratively: basic work, interdisciplinary work, programming and check results. For the successful execution of data-driven validation, the success factors: data origin, acceptance, data quality, knowledge about data and combination of domain knowledge must be considered.

Keywords: *industry 4.0, digital twin, product generation engineering (PGE), decision making, internet of things (IoT)*

1. Introduction

Requirements for new product generations are derived indirectly from information regarding the use of reference system elements in the customers production. This information travels from the machine operator via his supervisor to the machine supplier's sales department. They then communicate with the sales manager, who then passes the information on via the product management to the development. The described information management process results in a "silent mail" principle which results in the loss of information. In this paper, a case study at TRUMPF Machine Tools is used to address the hurdles to overcoming the silent-post principle. Information, especially feedback from customers at the machine operator level, is extremely valuable for the validation of requirements for new product generations.

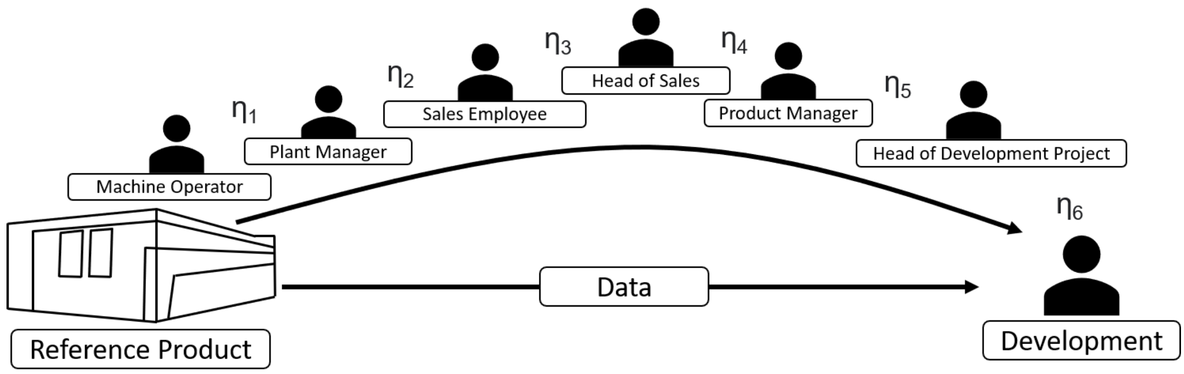

Figure 1. Information flow from the reference system element to the development

In any transition where information is transferred, there is a risk of changing information or loss of information. A study showed that only 20% of the original information arrives at the final recipient if there are more than five transitions in between (Hinterhuber 1993). Central decisions for the further course of development projects are thus mostly based on subjective assessments of individual actors or groups. By collecting and analysing usage data of reference system elements, information does not have to be passed on via various interorganizational areas but can be used directly. Many companies already collect large amounts of data. However, the mere collection and storage of data does not enable developers to use described data for analysis purposes. In order to be able to actively use data, comprehensive enablers are required. Adequate methods and processes must be developed to enable developers to use these forms of data in the development process. The use of reference system elements for data-driven validation of requirements therefore has a high potential for gaining a better understanding of the use of systems in the field.

2. State of research

2.1. Product generation engineering

The model of PGE - Product Generation Engineering according to Albers describes the development of new systems. Each system development is based on a reference system (Albers et al. 2015; Albers et al. 2019d). A reference system is defined by subsystems that already exist or are under development as well as their documentation. Elements of a reference system can therefore be design models, requirements or information from validation processes. They originate from the company's own predecessor models, other product lines, competitor products or research projects (Albers et al. 2019d). A new system generation is developed on the basis of the reference system through the combination of carryover, embodiment, and principle variation of subsystems (Albers et al. 2019c). Contents of the reference system are used as a basis for further development activities according to the variation operators (Albers et al. 2020). Figure 2 shows an example for the understanding of the reference system.

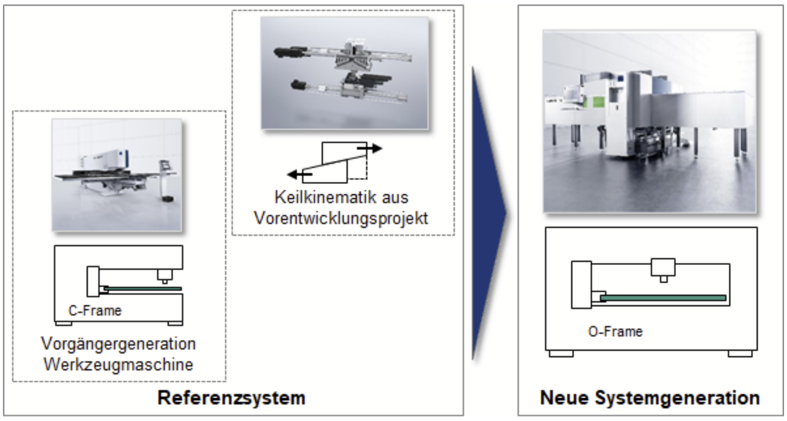

Figure 2. Stamping machine with elements of the underlying reference system (Albers et al. 2019d)

A principle variation is shown by the change from a C-frame to an O-frame whereas the adoption of the wedge principle from the predevelopment project represents a carryover variation. The punching unit was developed with an embodiment variation. The goal is to obtain differentiating features of the new product generation in relation to the reference system through new development components, in the sense of principle or embodiment variations. According to Albers et al. the economic success depends on the design of the differentiating features of a new product generation (Desai et al. 2001; Albers et al. 2015). The development risk is significantly related to the characterizing features of the reference system and tends to decrease with an increasing share of carryover variations (Alber et al. 2017). If reference system elements originate from products that are already used in the field, usage data can be collected and stored. Consequently, a large amount of data regarding the reference system

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elements is available for the validation of product generations that are currently in development. Consistent with the logic outlined above, analysis activities based on the data described above tend to reduce the development risk. Variations in shape and principle in particular require extensive validation activities (Albers et al. 2019b).

2.2. Data-driven requirements management

The majority of requirements management activities focuses on involving system users, highlighting their needs and using their feedback. In conventional requirements management, methods such as interviews, workshops, benchmarks and focus groups are typically used to gather data (Pagano and Maalej 2013). The system triplet of product engineering can be used to describe the development of technical systems. It describes the transfer of the system of objectives, consisting of requirements, goals, and constraints, via an operation system into an object system (Albers and Braun 2011; Bursac 2016; Ebel 2015). Requirements can be divided into functional and non-functional requirements (Liu and Palen 2009; Birkhäuser et al. 2009). According to the understanding of Bursac et al. functional requirements represent functional scopes of engineering generations (Bursac et al. 2021). Non-functional requirements correspond to quality requirements that need to be backed up after an engineering generation has been manufactured. Engineering generations can be understood as maturity levels (Albers et al. 2019a). Prevailing framework conditions justify the topicality and origin of functional requirements and quality requirements over several product generations (IEEE 1998; van Lamsweerde 2000; Bursac et al. 2021).
The subject of data-driven requirements management is how developers and analysts can use implicit and explicit data to identify, prioritize, and manage requirements. Promoted by the consequence of digitalisation in the engineering process the amount of data which can be gathered and stored will increase (Bharadwaj and Noble 2017). New technologies such as Data Mining allow developers to get deep insights into generated datasets. These insights have a high potential to support the decision making in the development process (Wu et al. 2014). In the future, requirements management decisions will no longer be stakeholder-driven and based on intuition (Maalej et al. 2016). Rather, the trend of extensive data collection will lead to user-oriented and group-based decisions. The process of decision making will be supported by analytics from a wide variety of data sources in real time (Nayebi and Ruhe 2015). The majority of decisions are still made based on intuition and experience (Davis 2003; Dumitrescu et al. 2021). The amount of data available can help minimize the subjective nature of stakeholder-driven decision making. With the increasing need for agility in development processes, the process of decision making is changing (Moe et al. 2012). Requirements are developed and implemented incrementally. Consequently, decisions in this context are based on the expansion or limitation of the system of objectives in development. Fundamental to the success of data-driven requirements management is the shift away from reactive approaches to proactive or real-time decision making. The goal is to incrementally develop the system of objectives by gaining deep insights into the customer-side usage structures of previous product generations (Maalej et al. 2016).

2.3. Big Data Analytics

Big Data Analytics is the use of advanced analytical techniques on Big Data sets. Big Data exceeds the capacities and capabilities of conventional systems and methods. It enables new ways to analyze questions that were previously difficult to answer (Russom 2011). According to Klein et al. Big Data is defined by the four V's Volume, Velocity, Variety, and Veracity (Klein et al. 2013). Advanced Analytics describes a collection of techniques and tools from Predicitiv Analytics, data mining, statistical analysis and complex SQL. Information generated from these analyses enables decision makers to optimize the process of decision making. For this purpose, predictive analytics describes the use of historical data to predict future customer behavior and trends (Mosavi and Vaezipour 2013). In the context of mechatronic system development, for example, this can be used to estimate the future use of functions. In addition to the evaluation of historical data using statistical models, predictive analytics can also be understood as the use of machine learning algorithms to recognize patterns (Shmueli and Koppius 2011). The use of data analytics to support decision-making processes is fraught with difficulties. In a study on data-driven decision making, 60% of respondents said they

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found it useful to use data and analytics to generate insights into customer behavior. However, only 13% of the organizations surveyed use data to generate insights (Zakir 2015).

3. Research questions and methodology

Previously discussed chapters indicate a high potential for the use of data from reference system elements to overcome the "silent mail" principle. Data-driven validation of elements of the system of objectives represents a key tool in this regard. Despite extensive literature in the described research areas, it has not yet been considered which success factors can be identified for the validation of requirements of new product generations by analyzing usage data of reference system elements. In the course of this research work the following research questions are answered:

1. Which activities are necessary for the data-driven validation of functional requirements in the development of mechatronic systems and what efforts are they associated with?
2. Which success factors can be identified when analyzing usage data of reference system elements for the development of mechatronic systems?

Methodologically, the procedure of the present research work is based on the Design Research Methodology (DRM)(Blessing and Chakrabarti). The focus is on the descriptive study I, in which research question 1 is answered in chapter 4 by analysing the carried-out use cases with focus on the necessary activities. The activities are derived by analysing the distribution of time effort required to perform such analyses of usage data. Research question 2 is answered in chapter 5 by identifying success factors which derive from the previous described understanding of the necessary activities. The case study consists of five use cases which are conducted at the company TRUMPF GmbH + Co.KG. For this purpose, usage data of the case-specific reference systems from the company's internal analytics framework are used to validate functional requirements in a data-driven manner. In this context, the activities into which the process of data-driven requirements validation can be categorized and the success factors to be identified in this context are presented.

4. Activities in the process of data-driven validation of functional requirements

As mentioned, the case study focuses on the validation of functional requirements from current development projects in the development of mechatronic systems. The objects described here as mechatronic systems are laser cutting machines, punching machines and bending machines for sheet metal processing. To gain a better understanding of the activities required to carry out such analyses, the time required for the use cases is quantified. The time required results from the difference between the time when the question arises to the time when it is clearly answered. The effort required for analyses represents a central process variable for measuring efficiency. From the context that the benefit of analyses strongly correlates positively with the results of analyses and that the result of analyses can only be estimated before the analysis is completed, the need for control and reduction of the analysis effort arises. Depending on the type of question and the requirements addressed, differences in the comprehensiveness and operational execution of the analysis are to be expected. It can be observed that questions about the need for the realisation of requirements and thus for the use of functions, for example, always arise directly from the development projects themselves. Functional requirements that are primarily critical to the success of the development project are given high priority and are validated at an early stage. In addition to the question of whether or not certain requirements should be implemented using development resources, there are other questions motivated by the need to optimize existing systems or to refute existing prejudices against the frequency of use of certain systems. From the findings of the case study, the following activities can be derived for the analysis of usage data:

- Basic work
- Interdisciplinary work
- Programming
- Check Results

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Figure 3 shows the time required to perform analyses based on the use cases.

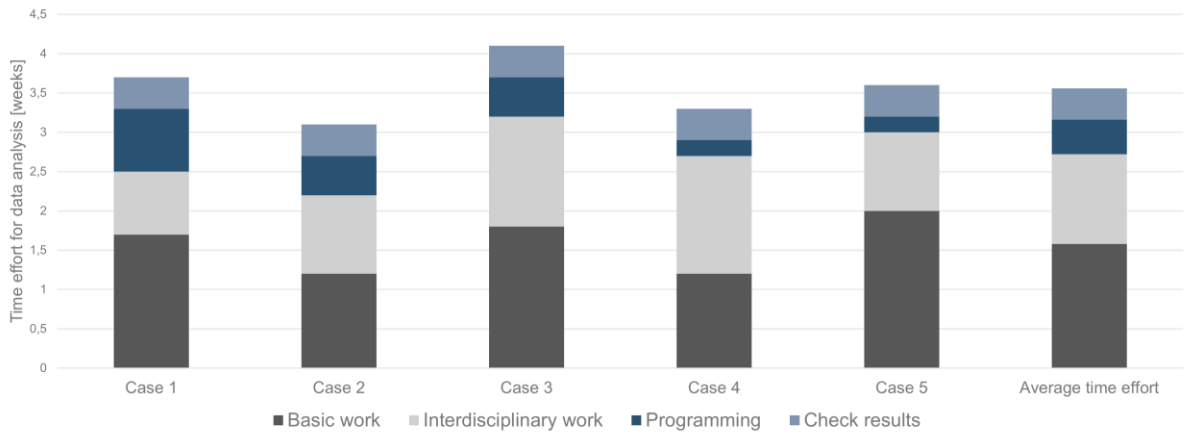

Figure 3. Workload in weeks for use cases of the case study

The *basic work* is the most time-consuming activity and takes about one and a half weeks on average in the course of the whole validation process. Activities for developing the analysis specifications and activities for initial testing of the data quality are subsumed under the basic work. It has been shown that the content and structure of the data provided are not primarily geared to optimization for the analysis application, but rather a pragmatic focus is placed on correctness for the execution of a machine program. Most of the times the answer to concrete questions cannot be tied to a designated parameter. As a result, parameter combinations must be worked out for analysis applications. The logical combination of different parameters allows the separation of the analysis case from the basic population. In addition, the necessity for the individual formation of parameter combinations results from the high variety of questions. As already described in the beginning, the effort of the basic work varies strongly depending on the type of question and the thematized requirements. The initial examination of the data quality can make a considerable contribution in terms of effort reduction through the potential early detection of errors. Misunderstandings or ambiguities with regard to the interpretation of analysis results can thus be prohibitively counteracted. It can be further observed that when analysed questions are successfully answered, new questions arise based on the results of the analysis. Questions that arise on the basis of initial findings from data analysis usually focus on a specific part of the first analysis. The previously performed basic work in the sense of the developed parameter combinations must then be changed or expanded if necessary.

Interdisciplinary work represents the second largest share of the time required for analyses. Due to the complexity of the topics and the novelty of such analyses of usage data in the context of the development of mechatronic systems, a great deal of effort is required for exchanges with experts. There is a strong dependence on the type of question and the requirements addressed. Certain questions are so special that even experts need several days to find the correct solution, for example in the form of a parameter combination. For their part, they have to enter an exchange with other experts in order to finally be able to report back a valid statement. Assuming that the capacity utilization of developers tends to be high, response times can be long in some cases. This in turn results from the individual prioritization of tasks.

Programming represents a small average share of the time spent on analyses. It includes all activities for the actual implementation of the parameter combination and execution of the analysis. The central challenges here are the implementation of the parameter combination and the performance of the code used for the analysis. A noticeable increase in efficiency was observed through the reuse of code fragments from previous analyses and by the consequences of the learning effect. In one particular case, adjustments to the code reduced the query time from over 16 hours to less than 3 minutes. In addition to the learning effect, the reuse of code fragments results in a toolbox of code fragments that can be adapted to new analyses with little effort. This makes a considerable contribution to the reduction of the time required.

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Finally, the *checking results* is the fourth activity. In addition to the knowledge of existing data and their structure, as well as the know-how for the practical execution of analyses, extensive knowledge is required regarding the design and the functionalities of the mechatronic system to be examined. The case study has shown that the final review of the analyses should always be carried out with experts for the systems in question. Conducted analyses of reference system usage data should not be viewed as a single source of truth. Rather, their added value is defined by their quality as a basis for discussion. The findings obtained must then be interpreted by experts in the development in the context of their underlying data and the steps taken execute the analysis. Decisions can then be derived from the interpretation of the analysis results. Figure 4 summarizes the descriptions of the activities using the example of Use Case 3:

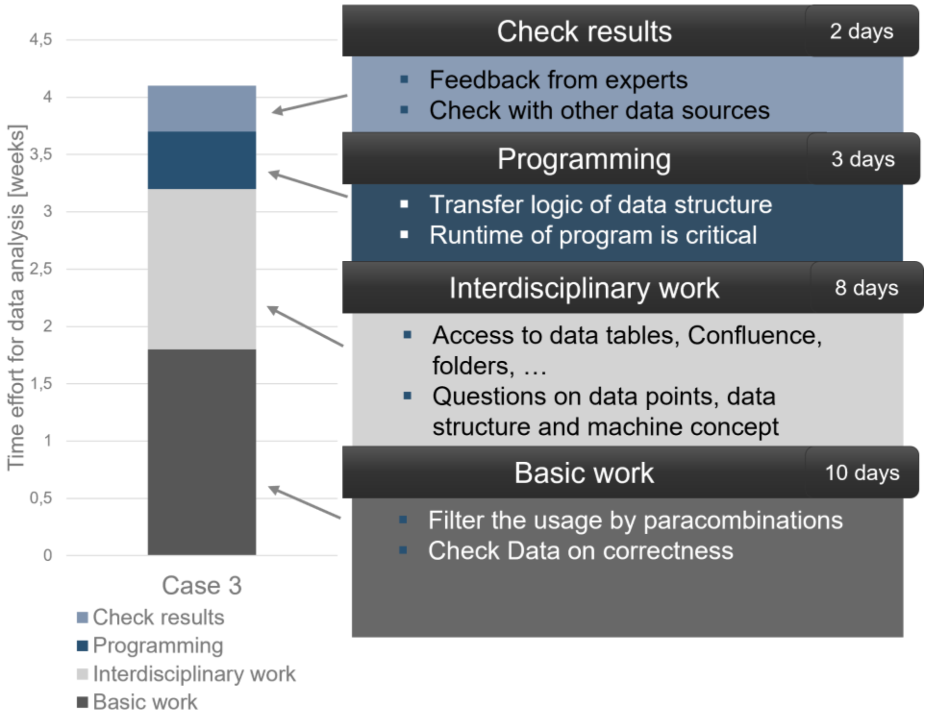

Figure 4. Breakdown of time required for analyses using Case 3 as an example

Contrary to what Figure 4 suggests, the analysis of data-driven validation of functional requirements is not a sequential process. The form of presentation is chosen because of the better visualization of the effort ratios. In fact, the steps described are run through in an iterative process. If, for example, it becomes apparent in the programming step that the parameter combination is incorrect, it must be tightened up during the basic work.

5. Success factors in analyses of usage data of the reference system elements

The identification of success factors for the analysis of usage data from the reference systems can be carried out on the basis of the use cases discussed in the case study. These arise against the background of the previously quantified effort required to perform analyses. The following success factors were identified:

1) Data origin

A fundamental problem for analyses in the described context lies in the way data is generated. The ability to interpret data correctly is directly related to the data generation. For example, the data of the source system under consideration originates from software products for the planning of machine occupancy for the execution of jobs. Thus, the data provides only limited information about the actual use of the mechatronic system. Furthermore, the following issues arise from this framework:

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a) It is not possible to trace whether the programmed machine assignments are carried out, since the data are not sent directly from the machine but originate in the CAM software.
b) Following the logic described previously under a) it is also not possible to comprehend how often a program has been executed.
c) Since the data originate in software products, no usage data can be collected when programming with software products from secondary suppliers.
d) By subsequent corrections or small adjustments of existing machine planning, supposedly same orders can exist several times. The versioning of the work statuses can be used here to determine the topicality of the machine planning to be compared.

2) Acceptance

The success factor described under point 1 made it considerably more clear how difficult it is for the viewers to interpret the data. The result of this is that during the study a certain skepticism could often be observed in the presentation of the evaluations. Accordingly, there is a problem of acceptance. In extreme cases, the acceptance problem described above manifested itself in a categorical rejection of any kind of data analysis using that specific data source. It could be observed that participants in the development of mechatronic systems tended to have more confidence in executed analysis activities with increasing knowledge concerning the background of the data origin. In order to make the background of the data origin tangible for all stakeholders, a disclaimer is introduced, which explains the problem areas for all participants at the beginning of a presentation. This allows viewers to classify and evaluate the data accordingly. This measure has led to a noticeable increase in acceptance.

3) Data quality

Across all use cases, an insufficient data quality could be determined. The exact manifestations of these insufficiencies can vary. The assignability between data points and the consistency of the content of data points to real products are central aspects for analyses against the background of the resilience of analysis results. An example from Case 1 is therefore as follows: The goal was to statistically evaluate the usage of a function on compatible mechatronic systems. The data analysis suggested a distribution of frequencies across five different machines. Only in feedback rounds with experts on the respective machine concepts it was determined that the implementation of the function could only be implemented in reality on two of the initially identified five machine types. Refinement of the parameter combination is thus iterative. Data quality problems can only be identified as such when analyses are performed on the basis of these data. Consequently, depending on the degree of novelty of the process for the data-driven validation of requirements, increased data quality problems are to be expected. Based on the connections to the need for logical combination of parameters explained in section 4, the aspect of missing data becomes apparent. This assumption is strengthened, since for the majority at analysis applications no designated individual parameters could be found. In the extreme case certain analyses are not to be accomplished due to missing data.

4) Knowledge about data

It can be seen that up to the time of the case study, analyses based on usage data of reference system elements have rarely been performed. The number of active users is limited to only a few individuals. This is recognizable from the small amount of data analysis that already exists. In fact, the touch points for some areas of mechatronic system development are still so small that the existence of this data is unknown. The result of this is a lack of knowledge about the data itself. This circumstance is reflected in addition in the topic of not yet uncovered errors which already has been discussed. Nevertheless, it is to be stated that empirical values exist. Connected with this is the problem of the accessibility to these empirical values. For example, Excel tables exist for documenting the significance of individual parameters and their values. However, the contents of these tables are not documented in a uniform way, nor are they complete or is the actuality traceable. Sufficient documentation of the parameters and their values could bring immense potential for increasing efficiency, especially in terms of the interdisciplinary work. In addition, there is a lack of

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documentation of contact persons for machines and functions. For example, it is not obvious to a software developer who in the company has specific machine- or function-specific expertise. This results in efficiency losses in the sense that contact persons for specific questions can usually only be found via several stations.

5) Combination of domain knowledge

The results of the case study show that the actual performance of analyses requires combinations of knowledge from the following three domains:

e) Knowledge about backgrounds of data generation and data structure
f) Knowledge about the operational execution of analyses
g) Knowledge of machine concepts and functions

This circumstance can be derived directly from the identified activities. For example, extensive programming knowledge is required to be able to perform data analysis operationally. Mainly more complex questions cannot be answered with simpel web-based analysis interfaces. In addition, if parameter combinations are required, the only way to do this is via specially programmed data queries, since the existing infrastructure does not support such specific queries. Furthermore, extensive knowledge of the data must be available for the basic work activity. In particular, the meaning of the parameters and the associated values plays a central role in the development of parameter combinations. For the activity of results testing, a profound knowledge of machine concepts and functionalities of systems is required to be able to understand whether the facts represented by the data do correspond to the reality. If, for example, there are contradictions in the analysis of the use of several machine systems, i.e. if the machine types described in the analyses are not compatible in reality, the results of the analysis must be assumed to be falsified. Consequently, the underlying parameter combinations may have to be adjusted or there may be a conceptual problem with the parameters provided. It can be observed that these points cannot be united in one person. To be able to perform analyses, close cooperation with other experts is therefore necessary at this stage. This aspect contributes mostly to the activity of interdisciplinary work.

6. Discussion and outlook

There is broad consensus that the analysis of usage data of reference system elements provides development teams with new possibilities for validating requirements (Dumitrescu et al. 2021). In the future, decisions for the further course of development projects can be made based on usage data and thus replace the subjectively influenced processes of decision-making. However, development practice shows that the introduction of data-driven validation processes is accompanied by various difficulties (data origin, acceptance, data quality, knowledge about data, combination of domain knowledge). Data can only become effective as added value for development if actors in the development of mechatronic systems use it for analysis purposes. The mere generation and storage of data does not add any value to development, but only causes effort. A change is needed away from a high level of trust in anecdotal expert opinions toward usage data-based validation processes for decision-making. Trust in data analyses can be strengthened, for example, through positive examples in which the added value for development is made tangible to developers. In addition, developers must be trained through qualification measures regarding data analyses. The increase in knowledge regarding operational implementation can increase the attractiveness of using data for analysis purposes. Similarly, the improvement of data quality through consistent model elements and the increase in the amount of data through an expansion of the data integration level pay into the goal of increasing attractiveness. In this context, the continuous use of model-based systems engineering allows a continuous traceability of analysis results and thus contributes to the reduction of effort.
Limitations of the present work result from the scope of consideration of five use cases in the case study, which were selected exemplarily from two current development projects based on their criticality for the project success. Furthermore, the case study limits itself to one data source explicitly. For example, data sources that include customer data or other business metrics are not considered.

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Lastly the study primarily focuses on the development of mechatronic systems. Further studies should be carried out to evaluate if the described results also apply to other fields.

In order to enable future actors in the development of mechatronic systems to make decisions based on usage data of the reference system elements, the necessary information must be made available to them. In addition to the results of the present work, it should be considered what kind of information is required for analyses in the development of mechatronic systems. In addition, it must be investigated how information from reference systems can be systematically used to validate elements of the system of objectives across product generations. In the following projects, functions that are not used by customers will be identified by analyzing data from the reference system elements. Furthermore, concrete measures for development will be derived on the basis of the identified functions.

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