How can Data Analytics Results be Exploited in the Early Phase of Product Development? 13 Design Principles for Data-Driven Product Planning

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Completed Research

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Abstract

The megatrend digitalization turns mechatronic products into continuous collectors and generators of use phase data. By analyzing this data, manufacturers can uncover valuable insights about the products and the users. Especially in product planning, these insights could be used to plan promising future product generations. The systematic exploitation of data analytics results, however, represents a serious challenge, as research on the topic is still scarce. In this paper, we present 13 design principles for exploiting data analytics results in product planning. The results are based on a systematic literature review and a workshop with a research consortium. The evaluation of the design principles is demonstrated with a real case of a manufacturing company. The identified design principles represent a first contribution to a still scarcely explored research field.

Keywords

Data-Driven Design, Data-Driven Decision-Making, Product Planning, Data Analytics, Design Principles.

Introduction

The megatrend digitization is leading to a transformation of products: In this context, Porter and Heppelmann (2015) speak of smart, connected products, which are created by the increasing integration of hardware, sensors, data storage, microprocessors, software, and connectivity. Lee (2008) refers to these products as cyber-physical systems (CPS) because they integrate physical processes and computation. These systems can collect data about themselves and their environment and make it available for further analysis (Porter and Heppelmann 2015). The evaluation of this data opens up a wide range of potentials; however, the research by Brandt et al. (2021) shows that the improvement of future products is the most prominent application in the literature. This assessment is supported by Holler et al. (2017), who further state that analyzing use phase data generates the greatest value in the early phase of product development, i.e. product planning, since this phase is traditionally characterized by great uncertainties and primarily qualitative information.

However, the exploitation of use phase data is still hardly successful for manufacturing companies. Groggert et al. (2017), for example, state in their study that companies use only 6% of the available data to support business decisions. And even if data analytics results are available, only 37% are used in decision-making processes (Groggert et al. 2017). According to Lueth et al. (2016), this could be a consequence of the inability of companies to generate real insights from data: Only 32% of the surveyed analytics professionals and decision-makers say they are good at this. One possible solution to support companies in the exploitation of use phase data in product planning is the provision of so-called design principles. These represent "a recommendation or suggestion for a course of action to help solve a design issue" (McAdams 2003). Therefore, we raise the following research question:

What are design principles for exploiting data analytics results in product planning?

The paper is organized as follows: Following the introduction, the theoretical background of this paper is described. Then, the methodology for identifying design principles for exploiting data analytics results in product planning is explained. The subsequent section describes the results of this paper. Then, the evaluation of the identified design principles is presented. Finally, the results are discussed and the paper is concluded by addressing its contributions, limitations, and future research needs.

Theoretical Background

To create a common understanding, this section first defines the essential terms. Subsequently, related research on the exploitation of use phase data in product planning is analyzed.

Basic Concepts: Product Planning, Use Phase Data, and Data Analytics

Product planning is the first phase of the product development process. It deals with the identification of the success potentials of the future, product identification as well as business planning (Gausemeier et al. 2011). The results of this phase are the product plan, which describes the products to be developed as well as the schedule (Ulrich and Eppinger 2016), and the requirements list (Pahl et al. 2007).

The term use phase data describes the data that is generated during the operation of a product. For CPS, Beverungen et al. (2019) distinguish usage data, context data, and status data. Usage data describes how a CPS is used in terms of activities, duration, and intensity. Information about the environment of the CPS is stored as context data. Status data provides information about the status and health of the CPS (Beverungen et al. 2019). Similar classifications are provided by Kreutzer (2019) and Balasubramanian et al. (2016).

Large amounts of data are generated during the operation of CPSs. The collection and analysis of this data are enabled by data analytics. Organizations can extract knowledge from the data to understand the past and predict the future (Tyagi 2003). Data analytics is based on mathematics, computer science, and business analysis techniques (Porter and Heppelmann 2015). Reinhart (2016) additionally emphasizes the importance of domain knowledge in the application of data analytics.

Related Research on Exploiting Data Analytics Results in Product Planning and Development

The purpose of utilizing data analytics changes during the product development process. According to Bertoni et al. (2020), this is due to the decisions to be made in the respective phases. Following Kennedy et al. (2008) and Isaksson et al. (2015), a distinction can be made between the knowledge value stream for the early phase and the product value stream for the late phase of product development. The knowledge value stream is characterized by rather directional decisions, while the decisions in the product value stream serve to elaborate the details of the products (Isaksson et al. 2015). Therefore, Bertoni et al. (2020) argue that data analyses in the knowledge value stream are primarily used to inform and describe the situation, while in the product value stream they are used to compare alternative solutions and to simulate and predict product behavior (Bertoni et al. 2020). In product planning as the early phase of product development, data analyses thus help to obtain a clear picture of the situation to make well-informed decisions based on it. In later development phases, in contrast, analytics models shall provide decision-makers with concrete suggestions (e.g., regarding the parameterization of components), which they then only must confirm.

Numerous examples of decision support in the product value stream can be found in the literature. Bertoni et al. (2017), for example, use data from the usage phase to understand the behavior of the product under consideration in simulated usage scenarios and, based on this, simulate new concepts for improving the product and evaluate them using some key figures. The authors then compare the insights gained from the data analysis with the initial expectations of the users to detect false assumptions (Bertoni et al. 2017). Klein et al. (2017) take an approach to exploiting use phase data based on design automation and simulation.

They feed a simulation model with the data to determine design parameters and compare design solutions (Klein et al. 2017). Abramovici et al. (2011) present a diagnostic module based on a Bayesian Network that is learned with the use phase data. The module calculates the failure probability of a considered component for different parameter intervals.

For utilizing data analytics in the knowledge value stream, to which product planning belongs, Meyer et al. (2022b) propose a reference process model that includes four process steps for the exploitation of data analytics results, which the authors derived from the literature and expert interviews: Results interpretation, requirements derivation, idea generation, and product strategy update. As a concrete application of data analytics in the knowledge value stream, Riesener et al. (2021) show, for example, how they derive new requirements for a product based on undesired correlations uncovered in the analyzed data. To do this, they analyze the functional and physical architecture of the product concerning the undesired correlations to identify starting points for improvements. New requirements then aim at breaking the found correlations (Riesener et al. 2021). A similar approach is taken by Meyer et al. (2020). They use data to test hypotheses and subsequently try to influence the independent variable of the hypothesis in such a way that the effect on the dependent variable is strengthened or weakened. Existing approaches to exploiting data analytics results in the knowledge stream thus tend to focus on rather simple relationships between a few variables. However, this does not do justice to the exploitation of more complex data analyses that promise deeper insights and greater value (Porter and Heppelmann 2015). Building on these considerations, there is a need for action for a more detailed investigation of the exploitation of data analytics results in product planning.

Methodology

Our process for identifying design principles for exploiting data analytics results in product planning is based on the method for design principle development by Möller et al. (2020). The method aims to give researchers and practitioners executable steps to generate design principles.

The first step of the method is to formulate a solution objective. Here, the purpose of the design principles shall be stated concisely and precisely. Following the definition of the general direction of the research project, a specification of the research context is made. This is followed by the selection of an appropriate research approach. For this, the authors differentiate between a supportive and a reflective approach. In the supportive approach, the design principles are derived in advance of the actual design process (here: exploitation of data analytics results). Sources could be the literature or expert statements. In contrast, the reflective approach demands that the said design process has already been carried out. The design principles are then derived from the activities of the process. Here, it is possible to draw on one's own design processes or those carried out by others. Finally, the design principles are evaluated, e.g., through expert feedback in the form of interviews or workshops (Möller et al. 2020).

The formulation of the objective and the specification of the research context were addressed in the prior sections of this paper. To answer the research question, we chose to perform both the supportive and the reflective approach as this promised to generate deductive as well as inductive insights and, thus, strengthen our results. For the supportive approach, an expert workshop was conducted. The participants of the workshop were members of a research consortium that has been working in the field of data-driven product planning for more than 3 years. The workshop was conducted in advance of the exploitation of data analytics results with the consortium and served to collect the expectations, experiences, and requirements of the participants. The workshop was based on the four process steps for the exploitation of data analytics results according to Meyer et al. (2022b). Using the "World Café" method, the participants worked on two questions for each process: "What are the requirements for this process?" and "What tasks must be completed during this process to aid the successful exploitation of the data analytics results?". Following the workshop, the results were analyzed and searched for hints on design principles.

For the reflective approach, we decided to analyze real examples of the exploitation of data analytics results to derive design principles. As our research consortium had not yet exploited data analytics results, we chose to analyze the exploitation processes of others and, therefore, performed a systematic literature review (SLR) to find suitable articles. For the search string creation, we tested multiple combinations of the important concepts of our topic and their synonyms. Through iterative improvement, we formed the following search string: *("analytics" OR "big data" OR "data-driven" OR "data-based" AND "decision-*

making" OR "decision making" OR "decision-support" OR "decision support" AND "planning" OR "development" OR "design" OR "innovation"). Using the Scopus database, we searched for articles within the engineering subject area. We also restricted our search to open access articles. The search resulted in 537 articles which we screened on a title basis. The titles of 151 articles suggested a focus on the exploitation of data analytics results. Two researchers read the abstracts of each article individually and rated them regarding promising content related to our topic. If both agreed that a paper was not suitable, the paper was rejected; otherwise, it was included for further analysis. Following this assessment, the remaining 68 papers were fully analyzed for possible design principles for exploiting data analytics results. While nearly every article addressed the topic "data analytics results" or "data-driven decisions", most articles focused on automated decision-support systems and, therefore, could not provide answers to our research question. However, eleven papers contained hints on the desired design principles.

Following this, we merged the findings of the supportive and the reflective approach. For this, the identified hints were compiled and iteratively clustered until design principles emerged which were mutually exclusive and collectively exhaustive (MECE). The resulting 13 design principles are presented in the following section.

Finally, we evaluated the design principles in a real use case of a manufacturing company. For enabling the effective instantiation and application of the design principles, we organized them into a method. To support this, we used the necessary process steps for the exploitation of data analytics results proposed by Meyer et al. (2022b) as a framework: Results interpretation, requirements derivation, idea generation, and product strategy update. We matched these four phases and the 13 design principles to obtain the method. Consequently, each phase addressed multiple design principles. The resulting method and the utilization of the design principles are described in the evaluation section. After designing the method, we applied it in a workshop with a manufacturing company to evaluate it in practice, following the suggestions of Möller et al. (2020). The workshop aimed at exploiting existing results of a use phase data analysis for identifying necessary changes to improve the considered product. The instantiation of the design principles in the workshop and the workshop results are also described in the evaluation section.

Results

The research resulted in 13 design principles for the exploitation of data analytics results in product planning. Of these, two are based solely on the results of the SLR and four are based solely on the results of the workshop with the research consortium (WRC). Seven design principles build on both the SLR results and the WRC results. The design principles and their sources are listed in Table 1. For their formulation, we followed the suggestions of Gregor et al. (2020). Since the responsibility for exploiting data analytics results lies with product managers and planners and they are, therefore, both implementers and users of the identified design principles, we refrain from naming them for each design principle. For the rationale, we refer to the respective sources.

No.	Design Principles	Sources
1	**Create a heterogeneous team:** To achieve a well-balanced exploitation of the data analytics results in product planning, create a heterogeneous team, focusing on different hierarchical levels, different departments, multiple disciplines, and internal and external experts.	(Guerrero-Prado et al. 2021), WRC
2	**Contextualize the data analytics results:** To avoid wrong interpretations and conclusions during the interpretation process, contextualize the data analytics results by investigating the number and heterogeneity of examined customers and products, the quality and quantity of the collected data, environmental, temporal, and contextual factors of the data collection, limitations of the analysis and the actual meaning of the analytics results.	(Ramanujan et al. 2017), (Laña et al. 2021), WRC
3	**Highlight noteworthy aspects:** To emphasize the relevant points from the multitude of findings while presenting the data analytics results to the team, highlight noteworthy aspects like statistical values or specific KPIs in the diagrams provided.	(Nazemi et al. 2021), (Ritou et al. 2019)

4	**Reveal biases and subjectivity:** To prevent one-sided and misleading interpretations of the data analytics results during the interpretation process, reveal biases and subjectivity by investigating the preparation of the results, the intentions of the team members as well as by preventing early confirmation of existing assumptions, self-fulfilling prophecies, and twisting of the results into a desired story.	WRC
5	**Involve product experts when evaluating data analytics results:** To clarify the meaning and consequences of the data analytics results for the product, involve product experts when evaluating data analytics results to explain them, estimate their confidence, and derive implications and consequences.	(Hussain et al. 2021), (Guerrero-Prado et al. 2021), WRC
6	**Validate the interpretations:** To build confidence for making impactful strategic decisions in strategic product planning, validate the interpretations of the data analytics results by comparing them with existing domain knowledge, by checking their compatibility with known customer and user needs and existing assumptions of product management, and by checking their conformity with existing norms, laws and budgets.	(Hussain et al. 2021), (Pasichnyi et al. 2019), WRC
7	**Combine analytics insights and domain know-how:** To identify original and feasible new solutions for product improvement, combine the data analytics insights with domain know-how by involving domain experts with rich practical experiences and make them generate new solutions based on the data analytics results.	(Zhang et al. 2022), (Er Kara et al. 2020)
8	**Model new solutions:** To create a better understanding of the new solutions and their impact on the product before making a strategic decision, model the new solutions by visualizing the necessary modifications and resulting consequences in existing visual models.	(Zhang et al. 2022), WRC
9	**Perform a criteria-based evaluation of the solutions:** To select promising new solutions for product improvement, perform a criteria-based evaluation of the identified solutions by considering costs, benefits, risks, effects on the company, tailoring options, and implementation plans for each solution.	(Zhang et al. 2022), (Er Kara et al. 2020), (Gopalakrishnan et al. 2022), WRC
10	**Check consistency of solutions and data analytics results:** To ensure the exploitation of the identified improvement potentials, check the consistency of the solutions and the data analytics results by analyzing the solutions' impact on the results and by identifying future data needs to check their suitability in operation.	WRC
11	**Modify existing artifacts:** To specify the consequences of the data analytics results, modify existing artifacts by changing existing aspects (e.g., certain existing requirements) or adding new aspects (e.g., new requirements) in the relevant artifacts (e.g., requirements list).	WRC
12	**Emphasize data-related aspects:** To illustrate the validity of product-related artifacts, emphasize data-related aspects by labeling them, describing their origin and causes, and by specifying future aspects to be investigated with data.	WRC
13	**Summarize the process and the results:** To make the exploitation process and its results accessible for people not involved, summarize the process and the results by describing the use case, data collection, analysis, and exploitation in appropriate terminology for communication.	(Gopalakrishnan et al. 2022), (Tian et al. 2019), (Er Kara et al. 2020), (Zhang et al. 2022), WRC

Table 1. 13 Design Principles for Exploiting Data Analytics Results in Product Planning

Evaluation: Instantiation of the 13 Design Principles

This section first presents the method for exploiting data analytics results in product planning. Then, the method's application in a workshop is described.

Method for Exploiting Data Analytics Results in Product Planning

The method for exploiting data analytics results in product planning builds on the 13 identified design principles and organizes them in four phases. In the first phase "Results Interpretation" (addressing design principles 2-6), the data analytics results are contextualized, described, and explained. In addition, implications for the product are derived. Subsequently, the results of the interpretation are discussed. The results of this phase are success potentials for product improvement. In the second phase "Requirements Derivation" (addressing design principles 5, 11, and 12), new requirements for the product are derived from the implications of the data analytics results. This is followed by investigating the relations between existing and new requirements and making necessary modifications. The resulting requirements form the basis for the next phase "Idea Generation" (addressing design principles 7-11). Here, solution ideas are first identified and then modeled. Based on that, their effectiveness concerning the problem at hand is checked. Also, the ideas are evaluated using multiple criteria. The result of this phase are promising ideas for product improvement. In the fourth phase "Product Strategy Update" (addressing design principles 10-13), first, the implementation of the ideas is planned in the product roadmap. Then, the consistency of the changes in the product roadmap and the data analytics results is checked. Finally, the exploitation process is summarized. Figure 1 shows the process model and highlights the addressed design principles in the tasks column.

Application of the Method in a Workshop

The application of the method took place in an expert workshop, which was conducted with a medium-sized manufacturer of ventilation equipment. The company's CTO had asked whether it is possible to detect contamination of their ventilation units with the help of data analytics. For this purpose, the company had set up an experiment in which the contamination of the unit was simulated by applying different masses to the fan. In addition, a sensor had been attached to the outer casing of the fan to record the vibrations of the unit. The data analysis resulted in several diagrams showing the recorded frequency responses of the device for each attached mass. These diagrams were the input for the presented method.

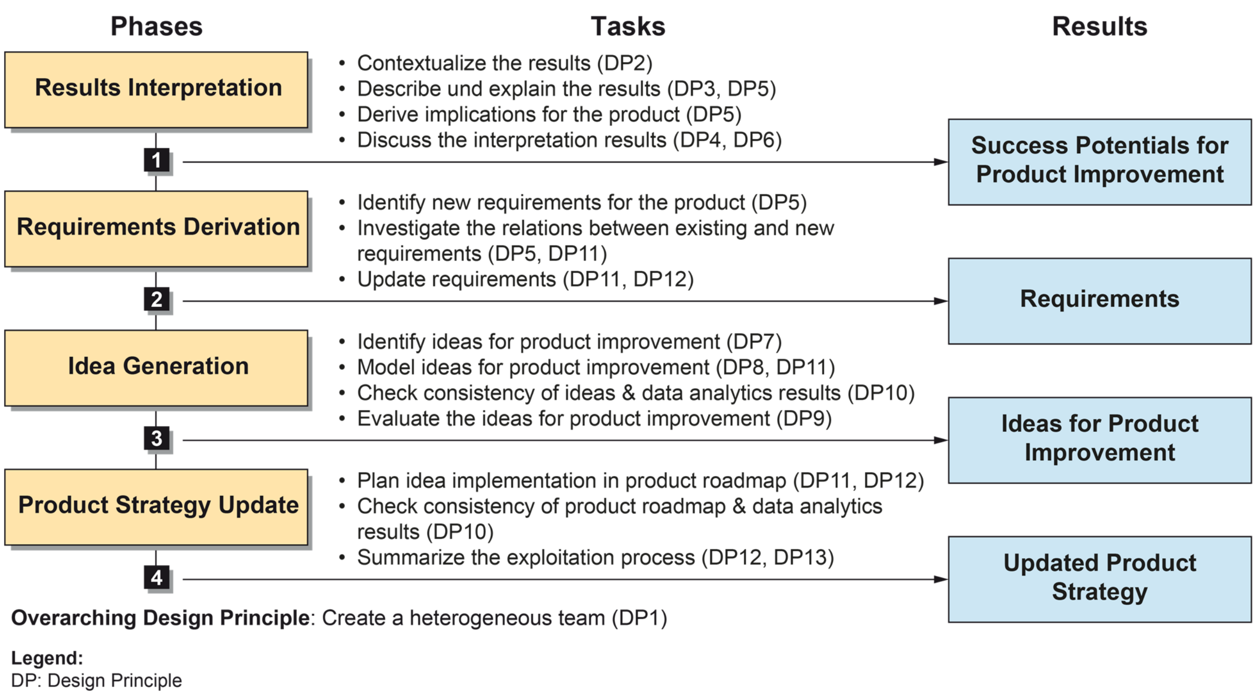

Figure 1: Method for Exploiting Data Analytics Results in Product Planning

The workshop was performed in an online meeting, using a concept board as the working area. The board consisted of one area for each phase of the method. For the interpretation, we created an interpretation canvas with a separate field for each task. For the derivation of requirements, we prepared an area for the identification of new requirements and another for the comparison of new and existing requirements. In the idea generation area, we set up a brainstorming and a modeling area. The latter contained existing models of the product architecture and the product environment that we could modify in the workshop. In addition, we prepared a cost-utility matrix for evaluating the generated ideas. For the product strategy update, we set up a portfolio for assessing the change relevance and complexity of each idea, providing us insights into the type of change (immediate action, minor release, major release, or new product generation), and a roadmap to plan the start of the development and the market launch.

In the workshop, the method and the built-in design principles proved to be very effective. Based on the provided data analytics results, a total of 15 new ideas for improving the product were developed and evaluated. Four of these ideas were selected and implemented in the product roadmap. The workshop participants also found the application of the method and the design principles to be very productive and convenient. The CTO stressed that the results obtained in the workshop are valuable for the company and the improvement of the product. He especially praised the modeling of the new ideas by modifying the existing models of the product architecture and the product environment because this created a deep understanding of the problem at hand and the consequences of implementing new ideas.

Discussion and Conclusion

The result of this paper are 13 design principles for the exploitation of data analytics results in product planning. They are based on the results of a workshop in a research consortium (supportive approach) and a structured literature analysis (reflective approach). The evaluation of the design principles took place in a workshop with a manufacturing company. This section discusses the results and concludes the paper.

Interpretation of the Results

A core theme of the design principles is the interpretation of data analytics results. Five of the 13 design principles (No. 2-6) address this task, which will be critical for the improvement of products in the future (van Horn et al. 2012) and thus a competitive skill (Isaksson and Eckert 2020). The other tasks for the exploitation of data analytics results in product planning, i.e., requirements identification, idea generation, and updating the product strategy (see Meyer et al. (2022b)), are directly addressed by a smaller number of design principles. This suggests that they will continue to be more heavily influenced by conventional product planning approaches and methods. Increasing the use of data analytics in product planning should, therefore, not lead to fundamental changes in these tasks, but rather to adjustments limited in scope.

This also becomes clear through a deeper analysis of the content of the design principles. None of them deals with the prescriptive exploitation of the data analytics results (e.g., for the direct calculation of a promising new product from the data). This result can be explained by the purpose of data analytics in product planning: It is used to describe situations and problems (knowledge value stream) and not for simulation and prediction (product value stream) (Bertoni et al. 2020). This observation confirms expert assessments that the analysis of use phase data primarily supports the identification of improvement potentials and not the identification of new product ideas (Meyer et al. 2022a).

Also, it is noticeable that some design principles are not fundamentally new but were also followed before the emergence of Big Data and Data Analytics (e.g., No. 1 "Composition of a heterogeneous team" or No. 9 "Criteria-based evaluation of solutions"). This is hardly surprising and follows from the argumentation above: Since data analytics in product planning serves primarily to describe the situation (Bertoni et al. 2020), the product planning process will not fundamentally change. However, the explicit listing of these proven design principles once again emphasizes their importance, which they do not lose even in the age of use phase data analytics.

Contribution, Limitations, and Future Research Needs

This paper contributes to the successful exploitation of data analytics results in product planning. As the results of the SLR show, existing methods for data-driven decision-making address only some of the 13 identified design principles. The collection presented in this paper summarizes suggestions from theory and practice in terms of best practices and organizes them into a common framework. With its focus on the exploitation of data analytics results, this paper addresses a scarcely explored research field because existing design principles in the data analytics context rather focus on the analysis of the data (e.g., see Begoli and Horey (2012)) and do not consider its exploitation. For researchers, the identified design principles thus represent an extension of the existing knowledge base. Managers, on the other hand, can draw on this collection of design principles to approach the exploitation of data analytics results in product planning in their companies more systematically and to derive more value from their data analyses. For them, especially the presented method, which builds on the design principles and significantly specifies the necessary process steps proposed by Meyer et al. (2022b), offers a promising starting point for exploiting data analytics results in product planning.

The obvious main limitation of our research is the small number of suitable articles found in the reflective approach of our procedure. Of the 537 articles initially identified with the SLR, ultimately only eleven articles contained references to design principles. Most of the articles found on data-supported decision-making in engineering focused on automatic decision support systems, which, however, are not suitable for the product planning phase (see related research). Of course, other keywords and the evaluation of other databases (besides Scopus) could uncover more suitable articles. Here, however, an effort-benefit assessment must be made. For example, with our search string, Google Scholar returns about 18,300 results. The evaluation of such a high number of articles would hardly be manageable. Moreover, many more unsuitable articles would delay and disrupt the research process. For this reason, we see our focus on the Scopus database as a pragmatic and suitable solution, while admitting that we cannot claim completeness. However, from our understanding, this is also not necessary. The reflective approach according to Möller et al. (2020) is, after all, about analyzing concrete examples of processes that have already been carried out and not about a complete overview of the literature. With this in mind, our SLR delivered us eleven concrete examples of the exploitation of data analytics results that we analyzed. Furthermore, through the workshop with the research consortium (supportive approach), we were able to uncover many more valuable hints that a few more articles probably would not have revealed. Therefore, we assume that our chosen combination of SLR and workshop is superior to a more extensive SLR.

Another limitation is the evaluation of our results. The presented method has so far only been applied with one company. The positive results from this workshop, therefore, do not yet allow any conclusions to be drawn about its application with other companies. However, we are confident that the method and the design principles are also effective beyond this, as they have emerged from numerous different sources and were not designed using only one company as an example.

Therefore, we see a need for future research primarily in the validation and extension of the identified design principles. The reviewed literature shows that research on the exploitation of data analytics results in product planning is still in its beginnings. For this reason, the further application of the identified design principles and the developed method represents a promising opportunity to generate new knowledge in this research field. Also, further workshops and interviews with industry experts should be pursued to identify additional design principles from practice.

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