

Micus, Christian; Schramm, Simon; Böhm, Markus; Krcmar, Helmut

Article

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Operations Research Perspectives

Provided in Cooperation with:

Elsevier

Suggested Citation: Micus, Christian; Schramm, Simon; Böhm, Markus; Krcmar, Helmut (2023) : Methods to analyze customer usage data in a product decision process: A systematic literature review, Operations Research Perspectives, ISSN 2214-7160, Elsevier, Amsterdam, Vol. 10, pp. 1-11, <https://doi.org/10.1016/j.orp.2023.100277>

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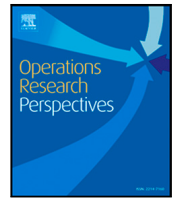
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Methods to analyze customer usage data in a product decision process: A systematic literature review

Christian Micus^{a,*}, Simon Schramm^b, Markus Boehm^c, Helmut Krcmar^a

^a Technical University of Munich, Krcmar Lab, Boltzmannstr. 3, Garching, 85748, Germany

^b University of Bamberg, Cognitive Systems Group, An der Weberei 5, Bamberg, 96047, Germany

^c University of Applied Sciences Landshut, Faculty for Informatics, Am Lurzenhof 1, Landshut, 84036, Germany

ARTICLE INFO

Keywords:

Customer usage data
Product development
Customer behavior
Big data
Data analytics
Product decision process

ABSTRACT

To remain competitive, companies must decide on new, desirable products. This can be achieved by integrating insights how customers use a product into the process of deciding on a new product. Currently, this process is primarily based on market research that can only reveal the intention of consumers. Through the digitization of products, companies have access to large amounts of customer data that allow the application of data analytics methods. We provide a taxonomy of artificial intelligence, machine learning and data analysis, so that the notion of data analytics can be defined. Thus, the terms customer usage data, as well as a generic, five-stage product decision process (PDP) are defined and differentiated from consumer data and the product development process. Eventually, we show which data analytics methods on customer usage data can be used in order to tackle current challenges within the PDP. We incorporate the results of our structured literature review by connecting selected examples to our concept of the PDP. Our insights help to apply the proper data analytics methods in the PDP and thereby address the interplay between product decision and product development. Finally, future research directions for data analytics methods on customer usage data are put forward.

1. Introduction

Big data has become a core theme in information systems research and practice [1–3]. Traditional manufacturers must deal with disruptive changes in their businesses in an environment of growing volatility of external influences, shorter product lifecycles, increasing global competition, and exponential technological progress [4–6].

The automotive industry is an example of this type of industry. The digitization of vehicles has increased sharply recently, leading to significant market dynamics and business model changes [7]. Digitization and the emerging connected car allow this industry to obtain large amounts of customer data. The challenge for these companies is to deal with the new data and apply the right methods to analyze the customer needs at the right time in the product development process [7–9]. Traditional manufacturers lack a representation of what level of analytics can be used in the product development process and what methods can be used to analyze the desired output. This way, the analyzed customer needs can be better used to develop new vehicles [8]. Only through the targeted use of the right methods for analyzing customer usage data can traditional manufacturers continue to be successful in the long term against new competitors that are structured more like an IT company [10].

From the conception of an idea to its implementation, data analytics can dramatically improve decision-making. Consequently, new product or service offerings can be developed quickly and tailored to customers' needs, giving businesses a competitive edge [9,11]. Data analysis of customer usage data is getting increasingly important in organizational processes as companies strive to integrate, prepare, and analyze data in real-time [11–13]. Despite ongoing breakthroughs in data processing, there is a shortage of understanding of how and under what conditions systematic data analysis enables businesses to make real-time product decisions [13].

The analysis areas for customer usage data and their informative value for product decisions is increasing, but no publications within a literature review framework have been investigated. Therefore, an illustration of which analysis methods in the literature are best suited is required to achieve the corresponding results. Only through the targeted use of the appropriate data analytics can the customer be better understood, and their needs identified. This way, innovations and decisions can be developed for successful and customer-relevant products. The goal is to demonstrate how different areas and analysis methodologies might impact product selection. The analysis areas for

* Corresponding author.

E-mail address: christian.micus@tum.de (C. Micus).

<https://doi.org/10.1016/j.orp.2023.100277>

Received 3 October 2022; Received in revised form 6 February 2023; Accepted 1 May 2023

Available online 5 May 2023

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customer usage data and their informative value for product decisions have not yet been investigated in the context of a literature review. Only a few authors have elaborated on the term product decision. Due to the proliferation of customer usage data in all industries, the trend is toward deeper analysis to understand customer needs and develop customer-oriented products. Therefore, this study analyzes which levels of data analytics can be applied within a product decision process (PDP, see Theoretical Background) [5]. The PDP is characterized by the potential to collect customer usage data at each step and analyze it to infer assumptions on the underlying customer behavior. Within the product creation process, the PDP decides which product to develop based on a defined customer with a diagnosed need for a product of which an apt design is to be deduced from prototyping.

This systematic literature review fills this need by helping create relevant research methodologies for various levels of customer usage data study, as well as their insights and possible applications.

In this context, this review answers the following research questions:

- Which analysis methods are used in the literature's customer usage data research field?
- Which level of data analytics is applied at what point in the PDP, and what results are obtained?

In this literature review, 79 publications (from 2000 to 2021) dealing with the analysis of customer usage data are identified. Appropriate approaches for the particular result needed are found by considering the output of the analysis. This study demonstrates that the paper's data analysis depth may be split into three main regions. Trends for future research can be identified based on the chronology of publications and the analysis methods used in the analysis areas. Eventually, we use the derived concept of a generic PDP to show, where data analytics methods can be applied to tackle challenges that currently exist in this process.

2. Theoretical background

In the following, some relevant definitions for this survey, such as PDP, customer usage data, or the generic concepts of data analytics, data analysis, artificial intelligence (AI), and machine learning (ML), shall be recapped. To understand the following results of the reviewed literature, customer usage data shall be the respective underlying data, which is analyzed via different tools from either data analysis or AI. Thus, the resulting application can be structured into different levels of data analytics. Eventually, a concise description of a PDP was found to be absent in the current literature, which is why it will be specified first.

2.1. The product decision process

Unlike popular conceptions of a product development process, which is a series of activities that a corporation does to create, design, and market a product [14,15], a clear description of the process of deciding which product to develop is rare in the scholarly literature. However, due to the digitization of products, companies become more and more capable of vast amounts of customer usage data. This usage data reflects the behavior of the current customer of a company, which does not necessarily equate the target customer of that company. This puts up an interplay between departments that may want to decide which products to develop based on an imaginary target customer and those that want to decide based on the current customer. We argue that beneath other important enterprise functions in a company, like quality or customer service, especially within the product decision function, customer usage data should be taken into account. In contrast to the PDP, pure decision processes were analyzed extensively by academic works, some of them go back more than 35 years. In general, defining a decision process is favorable for decision success and different types

of organizational structures are attached to patterns in their decision processes [16,17]. [18] states that a decision process for products should focus on completeness, meaning that every required step should be described. Furthermore, it should focus on quality, which means that the execution of the process steps is proficient. Eventually, such a process should focus on the important, such as the remedy of a product's weaknesses. Therefore, we analyzed scholarly approaches to decision processes in general and made a transfer to the decision process on products. A comprehensive overview of the strategic decision processes is provided by [19]. We focused on the activities that successful products featured in their decision process, as described by [18] in formulating the following definition of a PDP:

Prior to the product development process, the PDP begins and aims at defining the characteristics of a current customer, diagnose its needs for a product of which an apt design is to be deduced from prototyping. Thus, we define a generic process consisting of the following steps: 1. definition; 2. diagnosis; 3. deduction; 4. design; 5. decision.

Further description of the single steps of this process will be provided in Section 5. The PDP holds with regards to [18]. It is complete in the sense that it provides all steps required for the following product development process. The execution of all steps can be made in a proficient way, since they are characterized by the potential to collect customer usage data at each of these five steps and analyze it to infer assumptions on the underlying customer behavior. Eventually, the process focuses on the important, the remedy of weaknesses current products have, being unveiled by the analysis of customer usage data. In reality, the broader decision process occurs prior to the specific development process. Sometimes, both processes may also overlap, but deciding product category, form, or specification is desirable for a customer must start before any development can take place. In fact, this process does not even have to be allocated in research and development, but could also be conducted in marketing or corporate strategy [20].

2.2. Customer data and customer usage data

Customer or consumer data is defined as any recording of personal, behavioral, psychographic, and demographic information of consumers collected by a company [21]. We assume a case where a company collects only data from consumers of tools or products a company provides directly to a consumer, which thereby becomes a customer. The case of a company selling a vehicle to a customer or providing this customer with digital services during its usage of the vehicle is an exemplary case we would look at. The case of a company purchasing data of consumers that may be potential customers from a third party (like [22]) is an example for cases we would not want to look at. The difference between those two cases is, in parts, the goal of the analysis of the company, i.e., identifying the underlying behavior with which specifically the company's customers use the company's products versus identifying potential new customers from a group of consumers. Thus, we refer to customer data in the following. Subsequently, customer usage data is the activity recording with reference to a specific tool or product. It is thus a derivation of a customer's behavior in situations where both products are used, and recording is technically possible. Some authors thus refer to behavioral data in the same context, while others use the notion of engagement data [23–25]. This means that meaningful information can be retrieved from actual consumer data using well-established statistical and mathematical approaches, as well as ML or AI [26]. In the recent past, the scientific elaboration on methods for the analysis of customer usage data has experienced steady growth in various business fields like marketing or research and development [27,28]. The scope of the recording, collection and analysis of customer usage data is pervasive and many concepts could be outlined here. However, the scope of this paper is limited, which is why we will strictly limit our descriptions to methods to analyze customer usage data in the product decision process.

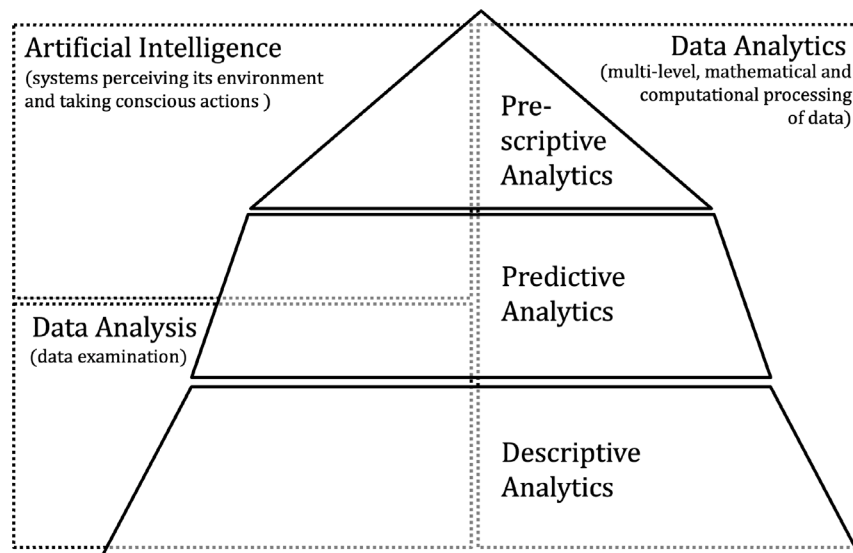


Fig. 1. Taxonomy of data analytics, data analysis, and AI.

2.3. Data analytics

The term data analytics is a commonly used concept that will be defined for the purposes of this review as multilevel, mathematical, and computational data processing [13]. Regarding the impact of data analytics on human decision-making, a hierarchy of descriptive, predictive, and prescriptive analytics is suitable. Descriptive analysis is the most basic type of customer usage data analysis. It entails summarizing and describing knowledge patterns using fundamental statistical methods like mean, median, mode, standard deviation, variance, and frequency measurement of certain events in big data streams [29]. At its foundation, predictive analytics is about identifying patterns and recording relationships in data. In this context, it includes forecasts and statistical models that determine future events based on historical and current data. Furthermore, prescriptive analytics combines predictions with prescribing attributes from the population [29–31]. Within a PDP, for instance, the past needs of a customer could be determined using descriptive analytics, while future needs could be forecasted using predictive analytics. Eventually, methods from the field of prescriptive analytics could be used to identify product attributes that will most likely satisfy the customer's future needs.

For the sake of this review, it is imperative to differentiate data analysis from AI because the two concepts shall represent two distinct groups of methodologies within the concept of data analytics. As detailed in the next section, data analysis is simply the examination of data, as opposed to the multilevel, mathematical, and computational processing of data that occurs at each level (descriptive, predictive, and prescriptive) of data analytics [32–34]. This differentiation is pivotal because, in the case of a PDP, all data analytics levels will come to play in analyzing customer usage data using methods from both fields: data analysis and AI. Fig. 1 displays a data analytics taxonomy with three levels: descriptive, predictive, and prescriptive, using methods from both fields: data analysis and AI. It is of primary relevance to determine which levels of data analytics may be applied to which stages of the PDP, as this mapping will reveal a gap in present academic research [33]. This literature review will later categorize the output of multiple authors before these data analytics levels, thereby providing the reader with a comparative understanding of which goal was aimed at by past scholars and how it must be seen in the context of product creation.

2.4. Data analysis, artificial intelligence, and machine learning

In descriptive statistics, data is analyzed by characterizing or describing observable data, which may or may not be drawn from a larger population [35]. In contrast, inductive statistics infer a sample's assumptions on the larger population. The observed data, which is a sample from a larger population, is an integral aspect of inductive statistics [36,37]. Inductive statistics are used to obtain the likelihood of a future event, and methods from this field deal with estimations and generalizations about the sampled population [36]. Descriptive and inductive statistics sometimes overlap within data analytics, for instance, in exploratory data analysis. Both characterizations of the observed data and predictions from a learned model can be analyzed or explored, for example, using data visualization [38]. ML is frequently used whenever a learned statistical model (see Fig. 2) is computationally exploited for inference [39]. It is a subset of AI that is defined as a system that perceives its surroundings and takes deliberate actions [40]. Generally, ML refers to any activity that a machine performs without being explicitly programmed, and it does so by employing algorithms to learn iteratively or train a statistical model [41,42]. Supervised learning refers to inference from a specific sample form (see Fig. 2) that contains both input and desired output. The mapping of specifically intended customer behavior characterizations to specific usage characterizations is fertile soil for supervised learning and is referred to as “labeled training data” [43]. Unlike supervised learning, no output characterizations are offered in the field of unsupervised learning, where rules and predefined goals define the goodness of a prediction [44]. Artificial neural networks are a commonly used architecture of a learned model in data analysis and AI, consisting of single computing units grouped in layers [45]. Eventually, the use of extra hidden layers, which enables the potential permutation of attributes from lower layers, shaped the concept of deep learning, which refers to a deep architecture of the artificial neural network. Thus, deep learning can be both supervised and unsupervised [46–48]. Fig. 2 shows those relevant concepts from the field of data analysis and AI, with ML and the supervised and unsupervised learning methods as subsets. Deep learning epitomizes a class within ML and can be applied to both ML methods outlined here, and ML uses inductive statistics to infer and predict the population. Eventually, this taxonomy does not represent all characterizations of every shown level, nor does it have a universal objective, but serves as a compilation of those concepts that will appear relevant in the context of this literature review. However, the taxonomy emphasizes supervised and unsupervised ML approaches that are useful

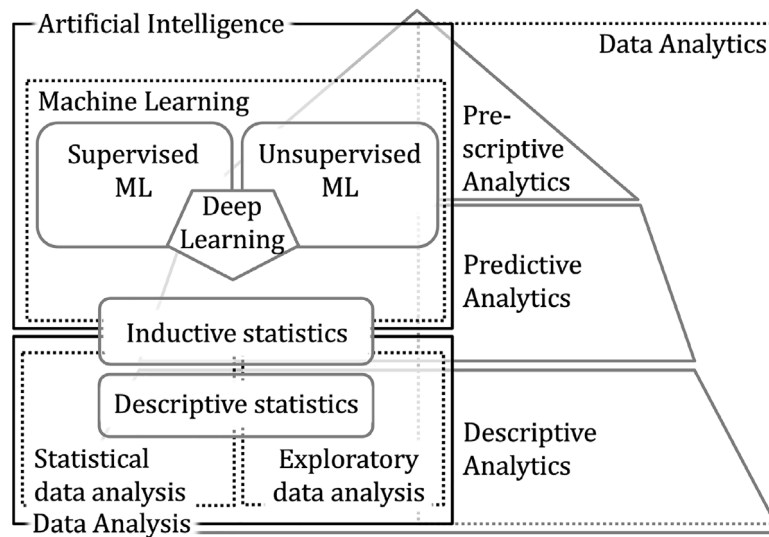


Fig. 2. Taxonomy of machine learning and data analytics.

in setting a PDP and placing them in context with, say, a class of algorithms like deep learning. So far, no other scholar has elaborated on this context and the interrelation of methods when dealing with product creation. Hence, the broad definitions given in this section are imperative for understanding the findings of this literature review in the following section and will serve as a basis for arguing about the gap in current academic research that this review addresses.

3. Design of the literature review

Following the systematic literature search process of [49,50], all relevant outlets were screened, and publications that analyzed customer usage data were searched. Subsequently, the studies regarding their methods and output were coded [51]. Afterward, the analyses of customer usage data according to the individual phases of the PDP were categorized. The search for relevant literature began with the top IS publications in the Association for Information Systems Senior Scholars' Basket of A-rated IS journals. The proceedings of highly ranked IS conferences were included to enrich the dataset with contemporary studies. Since customer data analytics has its roots in computer science research, the top five journals from the Association for Information Systems' particular interest group in decision support and analytics were included as they were expected to add to the technical perspective of analytics (Table 1). The abstracts of 160 publications were screened using the terms "analy*" AND "data" AND "user" OR "customer" AND "usage" AND "method" OR "approach" in titles, abstracts, and keywords. Only publications that dealt with customer usage data and analyzed it to gain customer insights were selected. The publications had to be published from 2000 or earlier, as the relevance of customer usage data was not yet that high. Forty-three publications from 160 publications were chosen. A forward and backward search was then conducted on the previously selected publications, adding another 36. In this process, dissertations were excluded. Finally, the sample for this review comprised 79 relevant publications (Table 1). The 79 relevant publications were analyzed from a concept-centric perspective. Hence, a concept matrix was established from the literature review results [49]. All contributions were studied to derive the various analytic approaches in consumer usage data that cover the unit of analysis holistically and comprehensively. For that purpose, the concept matrix considers the publication's main idea, the unit of analysis in question, theoretical and practical contributions, and the authors' research approach. The numerous concepts in the literature were then analytically aggregated in a concept matrix to highlight the important study areas and approaches in the literature on customer usage data analysis.

4. Findings

This section summarizes the insights from the selected and coded articles on customer data analytics. First, the articles were analyzed according to their industries in relation to their year of publication. Subsequently, the type of publication was looked into. Next, the methods used with the resulting output of the analysis in the form of a conceptual matrix were analyzed.

4.1. Overview of review findings

This section is a statistical summary of the identified literature's used methods and applied industries over time. The literature study shows that customer usage data analysis has its origin in the internet industry. The analysis focuses on how customers use websites to determine their interests [52]. Research interest in analyzing customer usage data has constantly increased since the 2000s (see Fig. 3). It can also be seen that the analysis of customer usage data continues to progress and can now be found also in other areas, such as mobile commerce [53], healthcare [54], automotive [55], finance [56], insurance [57], and education [54,58]. Less frequent areas were summed up under nonspecific [59], growing from 2013 to 2021. This review distinguished two methods for analyzing customer usage data in our iterative coding process: data analytics and AI. AI has been widely employed to evaluate customer usage data since 2015. Because of the rapid growth of a growing number of businesses and the widespread use of AI approaches, their critical role in assessing customer usage data is becoming clear. With the continuous increase in publications and the use of data in more and more fields, a clear trend can be observed in Fig. 3.

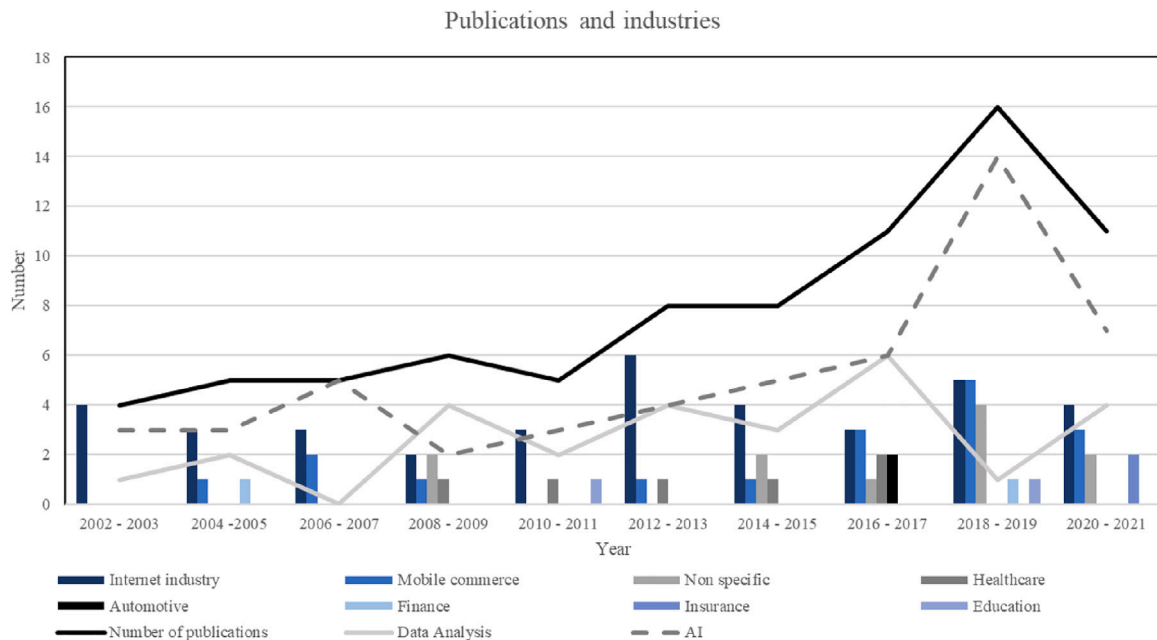
4.2. Types of publication

The 79 relevant publications were categorized according to their types [60]. This list is similar to that reported by Emerald publishing. It was discovered that most publications were either journal articles (49%) or conference proceedings (45%). Only 5% were book articles. Most publications were research papers or case studies (85%), and relatively few were literature reports (15%). Significant research has demonstrated the importance of analyzing customer data in various sectors (e.g., the internet industry, mobile commerce, healthcare, and finance).

Table 1

Search string and search results by outlet, hits, selected articles and forward (FW) and backward (BW) search results.

Outlet	Search	Hits	Selected	FW and BW Search
Basket of Eight	European Journal of Information Systems	3	2	
	Information Systems Journal	3	0	
	Information Systems Research	3	2	1
	Journal of AIS	0	0	
	Journal of Information Technology	1	0	
	Journal of MIS	5	2	1
	Journal of Strategic Information Systems	0	0	
	MIS Quarterly	1	0	
	ICIS	22	6	
IS Conferences	ECIS	17	3	2
	PACIS	19	2	
	HICSS	23	3	
	WI	15	0	
	AMCIS	19	3	2
Decision Support and Analytics	Journal Decision Support Systems	7	7	11
	Journal Decision Sciences	1	0	
	Journal Information Systems	3	3	
	Frontiers			
	Journal Expert Systems with Applications	15	10	11
	European Journal of Operational Research	3	0	
Other				12
Total		160	43	36
FW and BW Search				36
Total				79

**Fig. 3.** Search results by journal.

4.3. Share of used methods for analyzing customer usage data

After analyzing whether data analysis or AI methods were used in the first step, the types of evaluation methods used to analyze customer usage data in a concept matrix were intensively examined. Table 2 presents the top journals and IS conferences used to analyze customer usage data and classify them according to their use of analytics. The exemplary excerpt from the concept matrix shows that a large part of the customer usage data analysis lies in the statistical evaluation. The most basic type of data analysis is the use of descriptive statistics. Descriptive statistical methods were used for each type of analysis. Descriptive

analysis methods were used in [61] to analyze and compare customers' cell phone usage. This analysis can statistically determine how long each customer uses the cell phone. The analysis results are difficult to determine through qualitative surveys. The findings can determine customers' needs and optimally develop customer-oriented products. Based on the concept matrix, it can be observed that the analysis builds on each other. Exploratory data analysis is often performed in addition to identifying correlations and patterns in the data. In [62], the descriptive results were used to compare and correlate the data. The results serve as a guide for further in-depth analysis. Inductive statistics are often applied to perform deep insights and analyses of customer data.

Table 2
Concept matrix evaluation methods.

Reference	Data analysis			Artificial intelligence		
	Descriptive statistics	Explorative data analysis	Inductive statistics	Supervised Learning	Unsupervised Learning	Deep Learning
Smith K. A. et al. (2003) [45]	X	X			X	
Raphaeli O. et al. (2014) [46]	X					
Viet Nguyen B. et al. (2011) [47]	X	X	X			
Willing C. et al. (2017) [48]	X	X	X			
Albashrawi M. et al. (2019) [49]	X	X	X			
Yotsawat W. et al. (2021) [50]	X	X				X
Cheng X. et al. (2021) [51, 54]	X					
Zhang Y. et al. (2013) [55]	X	X			X	
Haupt J. et al. (2018) [56]	X	X		X		
Chen Y. -T. et al. (2020) [57]	X	X			X	
Das R. et al. (2009) [58]	X	X			X	
Chang S. E. et al. (2006) [59]	X	X				X
Feng Y. et al. (2017) [52]	X	X	X	X		
D'Ambra J. et al. [60]	X	X	X			
Liang T.-P. et al. (2008) [61]	X	X	X			
Bagloee S. A. et al. (2018) [62]	X	X		X		
Schäfer K. et al. (2013) [63]	X	X	X			
Turgeman L. et al. (2019) [64]	X	X			X	
Guo J. et al. (2018) [65]	X	X	X			X
Liu N. et al. (2018) [66]	X					
Other Publications	49	49	29	10	31	5
Total articles	75	72	40	12	42	8
Percentage share of total share of paper	96%	92%	51%	15%	54%	10%

It was noticeable that the amount of data to be analyzed was relatively tiny [63,64]. AI-based analysis approaches have become increasingly popular recently, with applications primarily in predictive analytics and, to a lesser extent, in prescriptive analytics. Analyses using AI methods are often applied to large data sets [65]. The concept matrix shows that unsupervised ML algorithms are commonly applied, with a trend toward expanding the depth of analysis of customer usage data. They recognize patterns in unstructured data and can, for example, identify clusters from vast amounts of data and thus perform segmentation [52]. The identified customer groups can be used to determine usage clusters based on customer behavior and size. Supervised ML algorithms are used for large amounts of customer data. There is always a dataset with labels from which the algorithm can learn. The algorithm then applies what it has learned to the dataset to be examined. This allows it to learn from mistakes and experiences and to make future mistakes or prognoses of how systems can be optimized [66]. Deep learning methods are used for profound data analysis. By applying deep learning models, decisions can be derived from customer usage data, and, for example, personalized recommendations can be generated from the usage data [67].

4.4. Value of the customer usage analysis

The benefits derived from analyzing customer usage data were examined in the publications for further analysis. The outputs of the analyses were inductively classified into six categories from the data-informed coded concepts of the systematic literature review according to [49,50]: forecasting, product development, optimization, hypothesis testing, decision impact simulation, and customer insights. Fig. 4 shows the relationships between the levels of data analytics, the used AI or data analysis methods, and the output obtained from the analysis. Table 2 shows the percentage distribution between these levels. Fig. 4

illustrates that the descriptive analytics domain is the foundation for analyzing customer usage data. Descriptive analysis was applied to all selected publications for data analysis and AI. Predictive analytics was conducted using both statistical and AI methodologies. According to relevant publications, 68.5% of companies use AI for predictive purposes. Only AI technologies are used to address the field of prescriptive analytics. The future importance of AI methods in customer data analysis can be recognized when combined with the trend toward using AI methods and the much more significant share of predictive analytics (Figs. 3 and 4). Furthermore, prescriptive analytics can be accomplished only by AI technologies. This repeatedly counteracts the use of data analysis by preventing access to prescriptive analytics.

Data analysis and AI methods were used in almost equal proportions. By analyzing the output of the application of data analysis and AI methods, it is noticeable that the distribution of the individual output shows which methods tend to produce which output. This shows which methods are particularly well suited to the analysis output. The analysis of customer usage data is most frequently conducted to determine customer insights. The publications also frequently use customer insights as a basis for further analyses. It is noticeable that even deeper customer insights can be analyzed through AI methods. For example, by applying cluster algorithms, user groups are formed to address the needs of individual customer groups [52,68]. In this way, the needs and behavior of customers can be more personal for specific customer groups. When statistical methods are applied, the usage behavior of the entire data set is analyzed, and holistic customer needs are derived [54]. The application of statistical methods usually requires much less effort. They are also frequently used to perform decision influence simulations. This often involves simulating current customer usage based on changes and comparing it to possible usage rates. For simple simulations of change, statistical methods can be used well and with little effort. Deep learning algorithms are often used

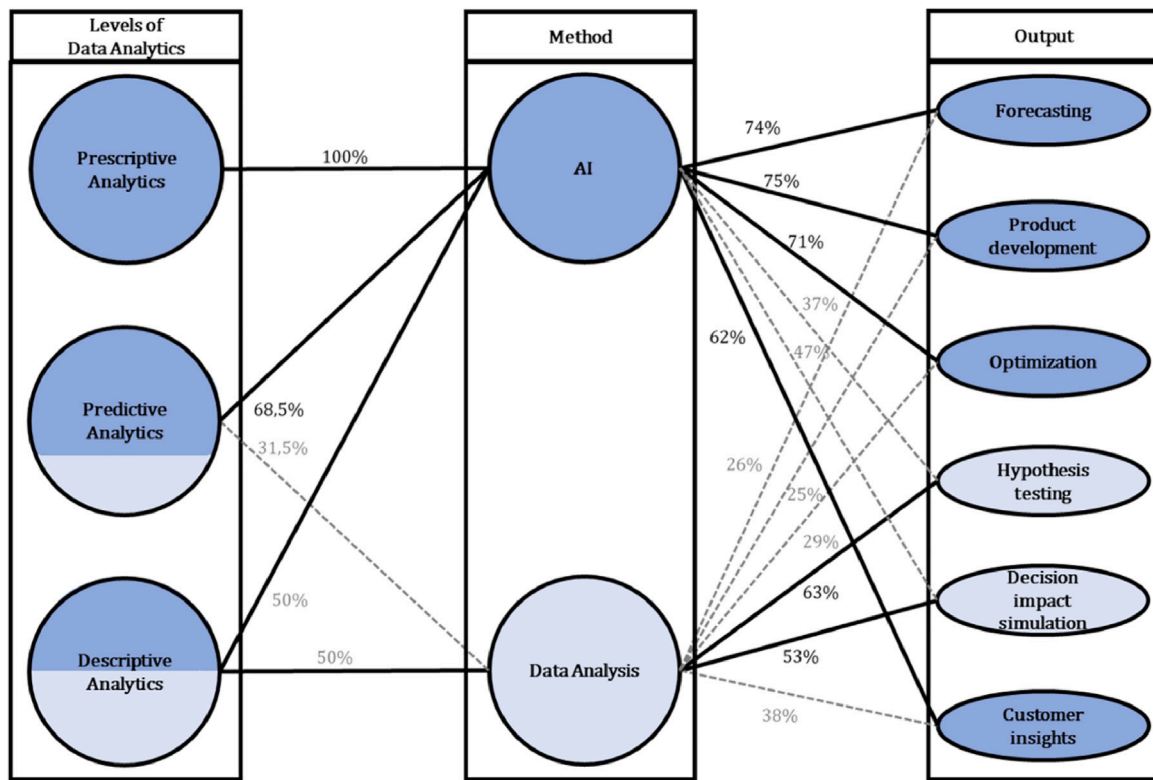


Fig. 4. Identified research methods for analyzing customer usage data.

for complex simulations of future events [67]. These often also derive decisions from the forecast. Previously established hypotheses have also been evaluated and tested using statistical methods. They are often used in exploratory data analysis [69]. Hypothesis testing is often used for preliminary analyses for later analyses using AI methods [70].

AI methods are increasingly used to a large extent for optimization and in developing new systems, providing even deeper insights into the customer usage. They are suitable, for example, for defining new functions and times of use based on customer usage data [65,71]. The goal is to interpret how another customer may use the feature in the future based on customer usage. Likewise, the function parameters can be optimized for customer use [66,72]. Statistical methods are used to analyze usage frequencies and identify underutilized features to develop and optimize functions [55]. Finally, the simulation of forecasts is also performed almost exclusively with AI methods. The AI method learns from past data and learns from its patterns what impact past data has on future experiences. Predictions about future events can be made from past data [73]. The application of AI prediction only works with a large enough dataset from the past. Statistical methods allow forecasting only with small amounts of data. Remarkably, more profound insights into customer usage data are almost exclusively investigated with AI methods. Nevertheless, data analysis is repeatedly used as a basis.

5. Toward a generic product decision process

The previous sections elaborated on what a generic PDP is and which methods can be used (see Theoretical Background). Critical findings when reviewing the literature are outlined in this context, and why current academic research lacks a concise definition of a PDP (see Findings). This section describes the analysis that was conducted in order to fill this gap. It will elaborate on a description of each step, describe the current situation and its challenges, and how product decisions are currently taken. By describing how the different levels of data analytics can be applied to each step, this section shall serve as

an attempt to fill the gap identified by this review. In the following, each PDP step as defined above, is detailed and complemented by real-world examples and applications. When reviewing the literature dealing with data analytics for customer usage data, it was discovered that most authors use methods from only one level of data analytics or combine specific methods from two or three levels in recurring patterns. Wong and Wei combined data mining from descriptive analytics with a predictive model [74]. Rarely all three levels of data analytics are combined; for instance, Jank, Dölle, and Schuh created a decision-making support system for product portfolios [75].

Recall that within the product creation process, the PDP decides which product to develop based on a defined customer with a diagnosed need for a product of which an apt design is to be deduced from prototyping. As defined above, the process consists of five steps. The PDP is characterized by the potential to collect customer usage data at each of those five steps and analyze it to infer assumptions on the underlying customer behavior.

5.1. Step 1: Definition

The first PDP process step entails the formal definition of the current customer of a company by analyzing its usage data. Thereby, matrix were intensively, descriptive analytics could be used to represent current customers by describing demographics, socio-economic constitution, or behavior during product usage [76]. Predictive analytics could be used to formulate assumptions of the future development of these factors. In contrast prescriptive analytics is less likely to be used, since the factors that determine the definition of a customer based on usage data cannot be influenced in most cases.

Challenges: Currently, the definition of potential new customers is frequently based on consumer data and usually marks the beginning of customer relationship management [77]. Customer usage data however, was not found to be used extensively during the formal definition of current customers. We see the challenge of multiple, diverging

definitions of customers existing in parallel in a company, for instance, in marketing on the one hand and research and development on the other hand. The descriptive analysis of the behavior of existing customers, coming, for example from research and development, could prevent marketing departments from sketching an unrealistic definition of potential new customers based on consumer data that, for example, describes the behavior of a group of consumers on the internet. Promising insights could also be found in the combination of descriptive and predictive analytics, for instance, when predicting the future behavior of a defined group of customers, as shall be described exemplary in the following.

Example: A vivid example of descriptive and predictive analytics in the step of defining the current customer can be found in the field of segmentation. Wong and Wei created an integrated customer segmentation model before predicting customized service offers [74]. In particular, the authors analyzed customer purchasing behavior data in conjunction with the purchase prices of online travel agencies. The decision support system used data mining to entail pricing data and characterize customers by predicting the potential subsequent purchases of a user.

5.2. Step 2: Diagnosis

Within diagnosis, deficiencies in the current market situation will be identified based on a previously defined customer. Whether a customer's specific needs are nonfulfilled, fulfilled, or exceeded will be answered in this step. Descriptive analytics can be used to describe the market situation, for instance, regarding seasonality or trends of its underlying time series [78]. Furthermore, predictive analytics could be used since the actual needs of a customer cannot be known but have to be inferred. Similar to step 1, the underlying factors of step 2 can, in most cases, not be influenced, which is why prescriptive analytics methods are not very promising.

Challenges: Creating a diagnosis of the current market situation is a core component of existing corporate strategy departments. Macroeconomic indicators are analyzed, and even consumer sentiment metrics are computed with methods from both descriptive and predictive analytics, for instance, for the prediction of whether customers will turn away from the company, referred to as *churn*, or not [79,80]. However, we found seldom examples of these methods being applied to data within a PDP [81]. In fact, customer usage offers great potential for the diagnosis step since it may be possible to unveil correlation between usage-behavior and market data, such as the usage of electric vehicles during times of high fossil energy prices.

Example: Deficiencies in the equilibrium of supply and demand are frequently analyzed with modern methods, such as analyzing customer sentiments based on online product reviews. Among others, Ireland and Liu applied descriptive and predictive analytics for sentiment analysis of online product reviews [82]. Their study used data generated via sentiment analysis from online product reviews to identify customer needs. The authors elaborate on descriptive analytics using maximum entropy or predictive analytics methods, such as a classification based on a support vector machine [82].

5.3. Step 3: Deduction

In the third PDP step, potential product concepts are deduced. The deduction is the most complex step of the PDP since it requires creating precise solutions for assumed problems that a customer is predicted to have. In doing so, descriptive, predictive as well as prescriptive analytics can be used to derive potential solutions in a data-centric manner. After the descriptive analysis of, for instance, existing product concepts, the potential volume of a new product of this concept

could be modeled, whereafter methods from prescriptive analytics can support the positioning of a new product in a company's portfolio.

Challenges: Certainly, converting the deduction step into a data-centric process would be by far the most challenging transfer. Next to the mere determination of market gaps and the consequent filling of those, innovative ideas frequently require an inventive step on top of that. However, recent advances, especially in the field of AI made advances in that regard, as shall be outlined in the following.

Example: Jank, Dölle, and Schuh integrated all analytics levels to create a decision-making support system for product portfolios [75]. Notably, the authors rested their prescriptive method on a neural-network-based classification model. They designed their antecedent pipeline on data cleaning using correlation analysis and time series forecasting to predict volatile market demands [75].

5.4. Step 4: Design

The design step of the PDP exclusively deals with the data resulting from the usage of one or more concepts or prototypes. It does not equate to the final specification of a product, such as its geometry or production concept. We will spare out the construction task of a prototype since it is not directly related to the product decision being taken later on. In a sense, we assume that any prototype is built in an ideal way and does not require any corrections. In reality for sure, prototyping is an iterative process, requiring thorough analysis of the prototype's usage data [83]. This iterative process however, has the primary goal of ideal prototype construction, not making customer usage data available for the PDP. In this phase, predictive analytics can model customer usage of the prototype and compare the results using descriptive analytics. Prescriptive analytics methods are less adequate in the design step of the PDP, since the prototype is already built at this step, and the task is to lever data resulting from its test-wise usage, not to re-construct it.¹

Challenges: Today, many product decisions rely on analyzing prototype data. The fourth step of the PDP is thus already integral to many companies and developers who have elaborated extensively on descriptive methods to analyze prototype usage data. In the past decades, however, data analysis methods were enriched with the field of AI, as described above. A major challenge today is to evaluate where, for instance, ML based methods can be applied in the design step.

Example: In prototyping, a significant trend is the digitalization of hardware and testing simulation [84]. Therefore, it is of paramount interest how data analysis and ML methods can be integrated into this fourth step of the PDP. Reiche and Timinger elaborated in 2021 on a process model for simulating the product lifecycle of different prototypes [84]. They used descriptive and predictive analytics methods to create a digital twin of the prototype. Descriptive analytics methods, such as frequency analysis, and predictive analytics methods, such as predicting customer acceptance or sentiment using neural networks, are widely used.

5.5. Step 5: Decision

The last step of a PDP is deciding on a product, or on one of the previously designed product prototypes. Descriptive analytics from the bedrock of this data-informed decision in the PDP. Information gathered in the preceding step could be concatenated to a customer

¹ Note that we do not assume that only one prototype is produced. In contrast, our framework is designed to also provide prototype usage data of multiple, different prototypes, each under the assumption of ideal construction to the following step. The iterative optimization process of prototypes however, shall be spared out.

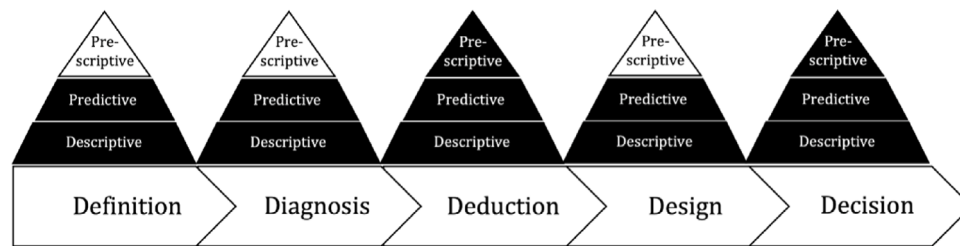


Fig. 5. Analytical framework alongside a generic product development process.

usage dataset, which can be compared to its predecessor from steps 1 or 2. Methods from predictive analytics could be applied, for instance, to re-evaluate volume potential forecasts from earlier in the PDP. Eventually, the product decision could be supported by prescriptive analytics, learning the sum of all earlier collected data and prescribing the most suitable price, for example.

Challenges: Today, results from descriptive and predictive models are already used to corroborate product decisions. Descriptive methods especially run rampant to portray which results of past surveys or market analysis produced. Sometimes, predictive models are also used when it comes to estimating which product may be most adequate given estimations of, for instance, future volume potential, revenue or gain in market shares [85]. A major roadblock for applying predictive models in this step of the PDP could be the perceived trustworthiness of predictions. This issue does not vanish when it comes to methods from prescriptive analytics. In fact, it could even aggravate. It is thus imperative to knock those barriers down, which may be possible using methods from the field of Explainable AI (XAI) or Interactive ML (IML), such as in [86].

Example: The pivotal step of the PDP is concerned with the decision for the right product, given the results from all preceding steps. Exemplary, one could prescribe operational decisions and evaluate whether they outperform baseline measures. As the third step of deduction, this step can again use all levels of data analytics to describe, predict, and eventually prescribe the ramifications and performance of human decisions. In 2019, Bertsimas and Kallus combined concepts from ML with operations research and management science (OR-MS) to prescribe optimal decisions in OR-MS problems. The authors used statistical decision theory to select optimal estimators for the prescriptions on the two-stage shipment planning data they aim at. On a descriptive basis, they assessed different k nearest neighbor (KNN), kernel and local linear methods, and trees and ensembles. In particular, they used nearest neighbor algorithms to determine clusters in customer behavior data before applying KNN regression to predict customer behavior. Notably, the prescriptiveness coefficient they proposed, which provides a measure of precision in the two-stage linear decision-making problem they face, contributes to the field of prescriptive analytics in the last step of a PDP [87].

PDP can be differentiated from product development processes because the product's disposal and final production do not play a pivotal role. However, the PDP culminates in the decision support stage, in which all data obtained and evaluated in previous processes are used to improve human decision-making. Notably, this procedure does not represent the entirety of the product development process, which would entail numerous other processes, such as testing [88]. Fig. 5 depicts the analytics framework alongside the generic PDP.

6. Contribution

This literature review contributes to the theory by providing an overview of the areas of analysis and the methods used in the research field of customer data analysis. The design of this literature review allows for a deduction of which methods are employed to accomplish

specific outcomes. The literature review matrix identifies gaps in current academic research, and future research areas can be deduced. Future scholars can now find significant trends in several industries and approaches for assessing client usage data.

As mentioned above, the state of the art of customer usage data analysis lacks a concise definition of a PDP. Thus, a PDP process is defined in this review, demonstrating which areas of analysis can be deployed at each stage of the product decision process. For each of the five PDP steps, challenges were identified and examples for how data analytics methods on customer usage data can be used were described. With the proliferation of data and the ever-increasing opportunities to use customer usage data, it is necessary to decide which analysis methods can be applied to which output. There are numerous methods for evaluating and analyzing customer usage data, but no representation of the outcomes of customer data analysis is required to make a product selection. This review contributes by sharing the approaches employed to obtain specific outcomes. Furthermore, it shows which areas of analysis can be employed at each stage of the PDP and which analyses should be used at which level of the PDP.

The results obtained from this review can be used in practice to illustrate the increasing importance of customer usage data in all areas. With the sharp increase in customer data, insights into analysis and their methods can be presented. This review benefits traditional companies that must deal with the new information channel of customer usage data. Given the challenges and examples of the PDP, we demonstrated how data analytics methods for customer usage data can be used to tackle them. It also demonstrates which procedures are appropriate for different types of analyses and which methods can yield the best results. The illustration of the data's depth can be used for research and provides practical advice on using the correct data and methodologies. The finding from this review illustrates which analytics and outputs can be used in PDP as the amount of customer usage data increases. This allows new customer insights to be created, and companies can better consider the customer's needs in developing innovations. The customer's interests can be integrated further into the development process, and the decision-making process can be improved. The decision process of new products is loaded with high uncertainty and has a significant meaning for enterprises. The right product decisions enable companies to target their development budgets on customer-value functions and respond quickly to new competitors and changes in the market. This allows companies to succeed in the market and provides a competitive advantage.

7. Future research areas

Building on the research findings described and the overall understanding gained in this review, this section presents areas for future studies. During this review, a surging application of AI methods in the field of customer usage data was observed (see Fig. 3). Further advances in AI using customer usage data are expected, and future research areas should focus on logically adjacent questions, such as "how can data privacy be assured when using data analytics on customer usage data?" or "how can result from prescriptive models on customer usage data be explained?" Especially the latter question refers to an emergent sub-domain of AI, which is referred to as explainable AI.

Based on the results of the literature analysis, it was possible to analyze how customer usage data is already being used in individual sectors and which methods are used. Underrepresentation of the supervised and deep learning methods was retrieved (see Table 1). Even though the underlying reasons for this insight are nontransparent, it can be stated that in other research fields, such as robotics or the financial industry, deep learning approaches are skyrocketing [41,42]. As outlined above (see Theoretical Background), supervised learning approaches focus on classification and regressions using labeled data, which is, per se, a viable setting for customer usage data. Questions of the kind “which lifespan for a product has to be ensured?” or “will a customer buy a subsequent product or not?” could be answered using supervised learning on customer usage data. However, labeling data and data cleaning before that is a laborious task, which may inhibit a tremendous increase in this field compared to deep learning.

Furthermore, future studies should explore how customer usage data can be systematically integrated into PDPs. To make a product selection, it would need to be specified which analysis results from the customer data analysis are required. Additionally, a comparison could be made between customer usage and study data results. As a result of all analysis findings, to the authors' knowledge, there is still no approach for combining customer research and usage data methodically into a product decision.

8. Limitations

Despite this attempt, this review has limitations. A descriptive literature review relies on existing and accessible studies (conceptual and empirical). The keyword search was limited to title, abstract, and keywords. Similarly, dissertations that interchanged forward and backward searches were disregarded. Selecting relevant publications is a subjective decision-making process. These issues are aimed to be avoided by independently cross-checking articles. Much subjective bias was attempted to be eliminated as possible by specifying the selection criteria accurately and equally. However, a residue is always present.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Christian Micus, Simon Schramm reports a relationship with Bayerische Motoren Werke AG that includes: employment.

Data availability

No data was used for the research described in the article.

Acknowledgment

Bayerische Motoren Werke AG (Germany) funded our research.

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