

# Customer Data Mapping - A Method for data-driven Service Innovation

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**Abstract:** Service providers nowadays face a complex situation, which is characterized by highly-demanding customers on the one and a plethora of potentially relevant data on the other hand. Data-driven service offerings need to be based on a solid understanding of available data in order to design personal value propositions. This research proposes a visual approach to build up data understanding from a customer perspective and highlights the potential of customer data. Based on the Customer-Dominant Logic, it develops the method “Customer Data Mapping” which supports businesses in establishing customer understanding through a structured process in a collaborative setting. It guides participants from capturing customer data along the customer journey to deriving customer understanding as the foundation for data-driven services.

**Keywords:** Customer data, personal data, data-driven services, service innovation, business transformation

## 1. Introduction

The need for customer orientation and personalized services [1–3] has resulted in a rising focus on personal customer data [1, 4, 5]. A wealth of customer data from connected people [6, 7] has emerged and it seems promising to use this data to build up a deep customer understanding as the basis of customer-centered service design [1, 8]. With rising importance of data and analytics, data-centric thinking becomes central to successfully leverage this data [9–11]. Data-driven services, such as smart services [6] and information- or knowledge-intensive services [12, 13], are all characterized by the intense use of data and algorithms [14, 15]. Data-driven service innovation [16] takes advantage of data and analytics in the whole process, for example for exploratory purposes or to design value propositions based on data [4, 7, 16].

In the exploration phase of service design, collaborative team settings strive to understand problem and opportunity space as the foundation for service innovation [17]. These innovation initiatives are mostly driven by interdisciplinary teams with varying levels of data expertise, also known as data literacy [18–20]. To fully take advantage of data, they must establish mutual understanding about data for the purpose of co-designing data-driven services [14, 18]. However, employees with direct access to data rarely participate in these initiatives [21]. In addition, businesses are confronted with structured and unstructured data in fragmented application systems [5, 8, 12]. As a

consequence, those who focus on service innovation mostly do not have an encompassing view on the available data resources [21]. Moreover, transforming data into value using analytics is a challenging task where communication barriers between data experts and the business side often complicate the design of data-driven services [11, 22].

Based on this problem space, methodological support for a systematic view on accessible data seems reasonable [12, 15, 16, 23]. Customer data especially requires knowledge about data sources as this data often needs to be aggregated across application systems to achieve the desired central customer view and thus an encompassing customer understanding [5, 24]. In collaborative design settings, novel approaches for data visualization can establish mutual understanding of available data across teams [18, 20]. This visual representation of data is perceived as crucial for communication, the construction and conception of services [11, 25]. Respective approaches must support beginners and data experts alike in the design process [18] and need to encourage

creativity [20, 25] to make optimal use of data. However, specific methods that offer guidelines on how to successfully leverage data for service innovation are rare, in particular regarding customer data [7, 15, 26]. Therefore, this research emphasizes the need to explore available data resources already in the exploration phase [17]. The identification of data resources should be strongly interconnected with the ideation process and value proposition design in order to increase efficiency: if intensive work is done during the conception of services, but is then blocked by insufficient data, inefficient iterations or a project stop might be the result. Understanding about customer data should be built up first and translated into customer understanding to facilitate value proposition design or even business modeling. For this purpose, two research questions have been defined:

**RQ1:** How can data understanding be improved in the exploration phase with a visual approach in collaborative settings?

**RQ2:** How can customer understanding be developed as the foundation for novel data-driven services?

Following a Design Science approach, this work strives to design a practitioner-oriented method, which links two main theoretical concepts. The Customer-Dominant Logic (CDL, c.f. [27, 28]) serves as theoretical lens to emphasize the need of analyzing

customer data from a customer's perspective as the foundation for data-driven service innovation. Concept Mapping (CM, c.f. [29]) from the field of learning psychology is utilized to develop a visual representation of data to creatively tap into the data space. Customer Data Mapping (CDM) as the resulting method has the following objectives: (1) systematic visual representation of customer data and relevant data sources and (2) visual support in the process of extracting information from data to build up customer understanding as the foundation for data-driven service innovation. To investigate the efficacy of the method, this research has used the restaurant industry as its initial application domain. This traditionally person-oriented industry represents a good example where opportunities and challenges of customer data can be observed well. Digitalization leads to a wealth of digital touchpoints from reservation to mobile ordering

systems, which results in rich, but also highly fragmented data in the restaurant tech-ecosystem [30]. The paper is structured as follows: the foundation chapter introduces relevant work in the field of data-driven service innovation; the design part outlines the conceptual elements of the method and describes the method's process; the evaluation section provides the results of the method's assessment. Finally, the discussion part summarizes the contributions to the field and leads to ideas about the method's future design.

## 2. Foundations

### 2.1. Data Understanding

The relevance of (big) data and analytics capabilities for service innovation is widely acknowledged in research [4, 6, 31, 32]. Understanding available data is central to build up customer knowledge and to successfully utilize this data for the design of data-driven services [12, 15, 21]. In data analytics, the term data understanding is used for

the process of building up detailed knowledge about available data. For example, the well-established cross-industry standard process (CRISP) for data mining emphasizes the careful evaluation of data at the beginning of an analysis with respect to the traceability of results and the efficiency of data science projects [33, 34]. Data understanding is inseparably interconnected to business understanding [33, 34] and builds the basis for the analysis and finally sensemaking [35]. In Information Systems (IS) research,

conceptual modeling techniques conventionally support in the process of building understanding of a domain [36, 37]. Different techniques model business processes, but also visualize related data structures [36, 38, 39]. A range of standards exists and ensures communication between stakeholders [40], e.g. the Unified Modeling Language (UML), data flow diagrams or Entity Relationship Modeling (ERM).

The application of traditional conceptual modeling techniques for data visualization in the early exploration phase of service design is assessed, however, as not appropriate. First, the main purpose of conceptual models is the analysis and precise representation of information requirements in IS development [36, 40, 41]. For this purpose, they are highly formalized and often contain additional elements, such as constraints, keys or relationship types, which are relevant for the system design, but also create complexity. The co-design of data-driven services, however, consists of stakeholders with diverse competencies. Different user characteristics, such as the level of data expertise, should be taken into consideration as they influence the successful modeling of data [37, 42]. Complexity that is not required in this early phase should be avoided so that even

beginners can easily comprehend the visualization elements without prior knowledge [25]. Second, the main target group of conceptual models are system designer and developers [41, 43]. Even if data models are used as a communication tool between system designers and users [37, 44], the main purpose of documenting requirements leads to a more technical data model [36, 43]. Practitioners therefore challenge the

value of traditional conceptual modelling for business stakeholders [36, 43]: neither can they be read intuitively, nor do they create ownership of data structures on the business side [43]. In the exploration phase, the visual representation of data must encourage users to act creatively [25] and help them determine how to benefit from data. Thus, it is questioned whether conceptual models can serve this purpose. Finally, in the world of big data, novel data sources and unstructured data, researchers question the relevance of current conceptual modeling techniques [42, 45, 46]. They call for novel approaches to extend modeling techniques from single data modeling to extract information from data and to create the foundation for predictive and descriptive analytics [45, 47].

## 2.2. Data-driven Service Innovation

Service innovation is defined as a “rebundling of diverse resources that create novel resources that are beneficial (i.e. value experiencing) to some actors” [31]. Data-driven service innovation (DDSI) includes data and analytics in this process [16]. It represents an innovative research field with rising attention [4, 8] in service design [12], service engineering or data-driven business modeling [9, 48]. Existing literature provides only a few visual approaches, which focus on data representation in collaborative settings (e.g. [14, 18, 21]). This is in line with an identified lack of methods in recent publications [7, 16, 18]. An overview of contemporary research reflects the novelty of this area, especially in approaching customer data for service innovation [16, 25, 26]. Significant research is outlined in the following: Kronsbein and Müller [18] designed the Data Innovation Board (DIB) as a visual tool for collaborative settings. This tool is strongly user-centered with the aim to explore the customer as “broad as possible”, but available data is analyzed from an organizational perspective instead.

Furthermore, DIB considers the possibility to deduct further knowledge of the user by using analytics. However, it does not support this step on a visual level. Böhmman and Kühne [11] then suggest the Data Insight Generator (DIG) as a communication tool between data scientists and business stakeholders. This method evaluates data quality aspects and data sources and pursues the objective to deduct insights from data in order to link them to concrete service value propositions. Kollwitz et al. [14] also designed a visual object, which they named “Data Vignette”. It consists of certain information of pre-selected data sets (e.g. data source, formats) and has the purpose of triggering ideas for data usage. The data canvas of Mathis and Köbler [21] has been developed for the identification and structuring of data resources as preparation for business modeling tools.

Finally, the Smart Service Canvas [49], a tool for data-driven business modelling, analyzes company data and points specifically to the analysis of customers’ tasks, context and environmental factors (e.g. temperature). However, building up customer understanding as additional knowledge is not purely the focus of these contributions. Moreover, guidelines are missing on how to derive customer understanding as additional knowledge from available data. Methodological approaches focusing on customer data in particular (e.g. [7, 23]) often seek to investigate the encompassing

value creation process of data or to develop data-driven business models (e.g. [23, 49]). Businesses are guided by process frameworks to support practitioners in the development of data- and analytics-driven services. Against this backdrop, Lim et al. [7] have developed a method to transform customer data into valuable services. Another example is the work of Zheng et al. [50], which considers user profile data, their usage and feedback data. However, getting an encompassing understanding of available customer data often plays a minor role in these contributions or is not considered at all due to preselected data sets that were used.

### 3. Methodology

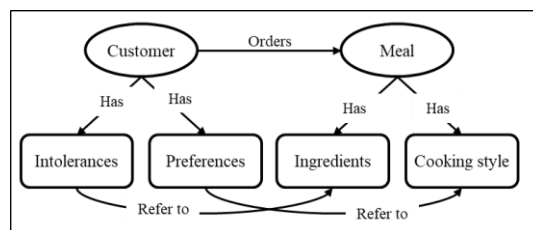
The CDM method was designed along the principles of Design Science Research (DSR), which is well-established in IS research [51, 52] and in service science [8, 53]. It offers methodological support in the form of a step-by-step process [52], evaluation guidelines [54–56] and knowledge contribution frameworks (e.g. [55]). DSR focuses on acquiring knowledge by building and evaluating artifacts [51], which are constructs, models, methods or instantiations that are built in an iterative design process. This

process aims at solving organizational problems. Following the DSR methodology, the CDM method design is grounded in a multiple step approach (c.f. [52]) as follows: The research problem (step 1) has been identified in a literature review that investigated methods in the field of data-driven service innovation. In order to build up domain understanding, workshops with stakeholders from the restaurant industry took place. This led to the definition of the research objective (step 2). The design phase (step 3) took advantage of conceptual elements to build a stable foundation for the artefact. A set of methods has been deployed (semi-structured interviews, structured surveys, workshops) to ensure a rigorously refined artefact. To expose the artefact to audiences in the demonstration phase (step 4), workshops and interviews were conducted to integrate different perspectives in the process. These applications also had the purpose of continuously evaluating the artefact through workshop participants and experts (step 5). As the artefact was still under development, the primary goal of this evaluation had been to identify improvements, but also to test its applicability and functionality in real-world settings [52, 56]. Several criteria [54, 55] were chosen for this purpose. Moreover, the method will be published to a scientific audience in the communication phase.

### 4. Designing the Method

#### 4.1. Concept Mapping

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**Figure 1:** Exemplary Concept Map

Concept Mapping is a widely adopted graphical tool for organizing and presenting knowledge [29, 43, 57, 58]. Concept maps originate from the field of learning psychology and are based on the theory that learning is a process of aligning new information to existing concepts [59, 60]. Figure 1 shows the basic elements of CM, which are (1) concepts visualized as circles and (2) relationships between concepts indicated by directed graphs. Objects (e.g. customers) or events are described by attributes (e.g. has food intolerances). Data-driven service design requires collaboration in cross-functional teams [14, 32] and a visual representation of data [20, 25]. Due to their intuitive visual communication, CM can be understood by various stakeholders, such as analysts, data modelers and decision makers, and thus create a common understanding in collaborative settings [43]. The process of searching and linking concepts to each other encourages creative thinking [29, 57]. Concepts maps have therefore been used as starting point to design the CDM method.

#### 4.2. Customer-Dominant Logic: Customer Processes & Customer Context

In this work, CDL serves as theoretical lens to emphasize the significance of customer data as the foundation for service innovation. CDL is a managerial perspective on marketing and business that focuses on serving customers individually by understanding each customer's "logic" [27, 28]. This "customer logic", as described in CDL, represents the history, presence and future of service consumption, the customer's individual aims and daily processes and is defined in this work as customer understanding. With rising amounts of digital touchpoints, customers produce data in each of their processes and interactions with businesses. This data (e.g. CRM data held by businesses), also called inside-out data, is valuable for building up additional customer understanding. However, CDL further emphasizes the active role of the customer who initiates and controls the service situation. This customer can also actively provide individual data (e.g. preferences for certain dishes). This outside-in [61] data creates customer understanding as well and should be equally considered in the service design process.

**Customer Processes:** Understanding the customer's processes is a key principle of CDL. Service providers must understand each customers' practices and daily processes embedded in their social system. In the field of service design, customer processes have been used intensively to manage interaction processes with the customer [62, 63].

Bettencourt [63] and Lim et al. [7] describe customer processes as a series of activities in order to accomplish a customer's goal (e.g. booking a table in a restaurant). Several methods, such as Customer Journey Mapping (CJM), have emerged to visualize those customer processes, e.g. [62, 64]. CJM is a strategic management tool that describes a service experience from the customer's point of view [64]. The increase of customer activities at digital touchpoints (e.g. table reservation system) leads to a data landscape that is characterized by disparate systems for data storage. The analysis of digital activities along customer processes is an essential element in the new method as it allows both a systematic view on customer processes and resulting data structures.

Similar to CJM, customer activities are examined in sequential phases (pre-sales, sales, after-sales) in order to achieve a more structured analysis process. Finally, the view on touchpoints has been incorporated for the analysis of relevant data sources.

**Customer Context:** Following the perspective of CDL, context is conceived as further describing customers and their current situation [65, 66]. Customer context has been embedded as conceptual element into the artefact to explicitly identify relevant information for the data-driven service design. It extends the view on available data and serves as an information category to deduct insights about the customer by combining and aggregating data, e.g. from the analysis of customer processes. It has the objective to identify customer attributes that can be extracted from available data and serve as entry points for subsequent prescriptive or descriptive analytics, such as mining methods (e.g. [67]). For example, based on the last restaurant visits, preferred restaurant

categories as a context attribute might reveal insights about an individual's preferences. As described above, customer understanding cannot solely be derived from available data (inside-out view, cf. [2, 61]). Customers might also provide valuable personal context themselves to a service provider directly (outside-in view).

### 4.3 Customer Data Mapping – A Method for data-driven Service Innovation

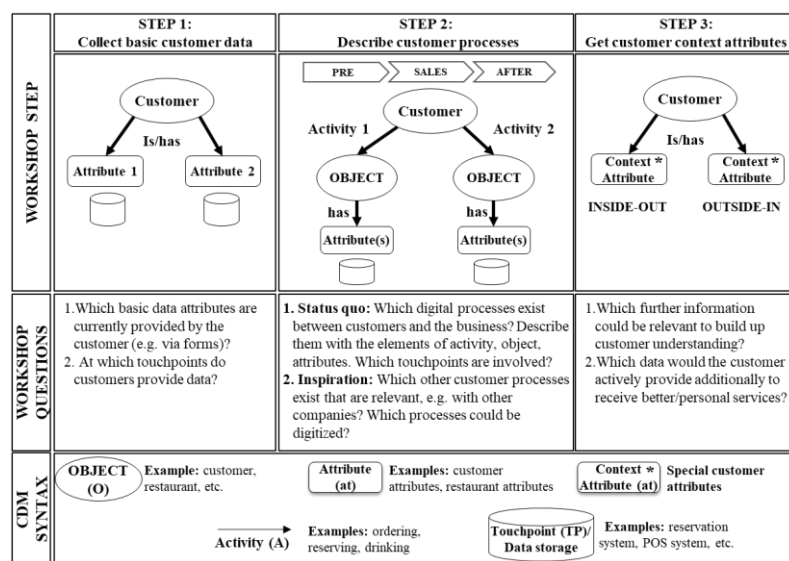
If businesses strive to take advantage of rising data potentials for the design of services, CDM offers guidance in understanding their data resources by analyzing customer data from a customer's perspective. It represents a process-based workshop method for

collaborative service design settings and takes place in the exploration phase. CDM has the following objectives: (1) systematic visual representation of customer data and data sources, (2) visual support in the process of extracting information from data to build up customer understanding as the foundation for data-driven service innovation. CDM goes beyond documenting existing data as it further facilitates creative thinking on how to extract information from data in order to interlink value proposition design stronger with data usage. Besides customers, relevant participants are service designers, business stakeholders and data analysts or developers from one or multiple companies. Following the method engineering guidelines of [68], the artefact consists of standardized building blocks derived from the conceptual elements of customer processes and context. Similar to conceptual modeling techniques, it models data structures, but does not possess the same level of standardization as described in [37]. However,

CDM incorporates several modeling rules, a certain grammar and a corresponding process model. To maximize simplicity and understanding across participants, CDM utilizes only a few elements that are grounded in the CM syntax (see Figure 2): concepts in the form of circles represent objects. Customers have relations with other objects throughout their processes, which contain activities visualized by arrows and another object. Finally, objects are described by attributes in the form of boxes. Customer attributes are further classified in CDM as basic customer attributes and context attributes. The latter are marked with an asterisk. Resulting content does not only de-

scribe customer attributes and relevant customer processes, it also models the underlying data structures. Media used for the modeling of customer data are paper-based texts and graphics by means of multi-color post-its and memo boards. The process model of the method is displayed in Figure 2, where different steps of CDM are guided by a moderator. These steps are not sequential and might contain feedback loops.

**Method Application:** Even if the application of CDM is not restricted to any particular industry, the testing has been mainly conducted in the restaurant industry due to the reasons described above. A first workshop with stakeholders was conducted with the primary purpose of screening customer data in the domain by describing customer processes using the syntax of concept maps. A second experiment took place with the CTO of a start-up to analyze the method's usability primarily from a technical viewpoint. The method has been further applied in the context of a digital transformation project of a German restaurant group with the objective to improve data understanding and to deduct novel ideas on how to benefit from increasing data sources. Finally, interviews and a workshop with service design experts aimed to challenge the method from a service design perspective. Applications in other industry settings were conducted to test the method's generalizability.



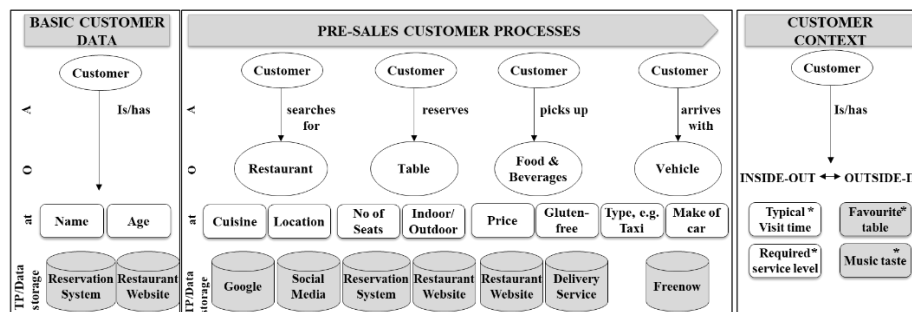
**Figure 2: Process Model of Customer Data Mapping**

An overview of the application settings is shown in Table 1, whereas Figure 3 provides examples of documented results.



| Overview of Workshops (W) and Interviews (I)  | Participants   |
|---|--|
| W1: Cross-industry Workshop in the Application Domain   | 12 Participants, e.g. Restaurant Operators, Industry Partner & Technology Providers          |
| I1: Interview with a Tech Start-up in the Restaurant Industry   | 1 Participant: CTO   |
| W2: Workshop with a German Restaurant Group in the context of their Digital Transformation Project                                      | 8 Participants: e.g. Director Digital Marketing, Digitalization Expert, Restaurant Operators |
| W3: Workshops with a German Marketing Technology Provider   | 10 Participants: e.g. Marketing Managers, Technical Service Provider                         |
| I2: Interview with a Service Design Expert  | 1 Participant: Director Co-Creation & Innovation, Consultancy Agency                         |
| W4/I2: Workshop and semi-structured Interview with Service Design Experts (Consultancy Firm, Innovation Lab, Startup for Data Services) | 4 Participants: e.g. Senior Innovation Consultants, Senior Strategic Designer, CEO           |

**Table 1:** Method Applications and Participants



**Figure 3:** Exemplary Workshop Results from the Restaurant Industry

Participants started to gather basic customer attributes (e.g. name, age or email address) that are currently available in one specific restaurant, e.g. in reservation systems. In a second step, they brainstormed about customer processes and possible touchpoints in the different phases. Participants started with digital processes of a customer with the chosen company in a status quo analysis. Due to the necessity to comprehensively

understand customer actions, the following inspiration phase screens further customer processes that could be beneficial to understand the situation of the customer, e.g. processes with other companies or processes that are currently not digitized. The pre-sales phase is used as an example in Figure 3 to show a few of the digital processes relevant in the restaurant setting. A process consists of the customer's activity (A) along with an object (O) and related attributes (at). A reservation, for example, can be described as follows: the customer reserves (A) a table (O) for four people (at) outside in the garden (at). After the first status quo analysis, the arrival of the customer with a specific vehicle was identified in the inspiration phase as an interesting process to look at to further understand the current customer situation. Finally, customer context attributes were worked out by participants. The visual structure of the process does not only offer a systematic approach for data visualization, it also encourages participants to creatively collect ideas about relevant attributes about the customer in the form of inside-out

customer context. This is achieved by looking at objects and attributes related to the customer activity. For example, characteristics of the ordered meal, such as ingredi-

ents or the price, provide further insights about the individual. Frequently avoided ingredients, such as gluten, help to further understand the individual customer. Examples are typical visit times, required service levels or the financial value of the customer. CDM aims primarily at identifying relevant context attributes to further describe the situation of the customer. In order to actually extract this information from data, descriptive or prescriptive approaches are necessary in a subsequent step. Data analysts, who often do not have the (complete) business understanding, therefore get valuable directions on which data they should focus on. However, following the CDL does not only require the knowledge of customer processes to build up additional customer understanding. Asking customers which information, they would directly provide for better-fitting services represents the final step of the method to generate valuable customer context from an outside-in view. Examples are diet preferences, allergies, the preferred table or music preferences. To sum up, CDM pursues the objective to identify context elements from the inside-out and outside-in view to highlight that the same information might be acquired from both perspectives, e.g. diet preferences. As a consequence, service providers need to carefully decide how they generate customer understanding for data-driven services.

## 5. Method Evaluation

To achieve rigorous results in the design process of the artefact, iterations of the method took place after each application. A mixed approach of naturalistic and artificial evaluation settings has been chosen for this purpose while a mix of research methods were applied (semi-structured interviews, structured surveys, workshops). As stated in Venable et al. [69] and Gregor and Hevner [55], evaluation of DSR can serve different purposes depending on the type of the artefact and the maturity of the application field. Due to the nascent field of data representation in the exploration phase, the main focus of this early assessment was to formatively test the method in real-world settings and to iteratively improve the artefact. The aspect of customer-centered data representation has been an experiment on how this focus allows participants to communicate about data on a common ground and to deduct customer understanding for novel service ideas. Furthermore, relevance and functionality of the method should be verified along with its contribution to real-world problems as demanded by Peffers et al. [52] and Hevner et al. [51]. Workshop participants and interview partners were selected based on their expertise in service design and their role in the specific industry setting. The selection of multidisciplinary teams was important to prove the method's capability of creating a common understanding for collaboration. The evaluation phase did not have the purpose of assessing the method on a quantitative level or to compare its performance with other methods. Such an assessment has not been perceived as reasonable due to high demand of organizational resources and the difficulty to reach comparable results in socio-technical settings with heterogeneous participants (c.f. [69]). Structured surveys were used to systematically collect feedback of partici-

pants. This measurement took place after each experiment. A criteria-based approach has been chosen following DSR and method engineering [54, 55, 68]. These criteria guided the evaluation process. In the following paragraph, the participants' feedback is described in accordance with the criteria for assessment.

**Functionality:** Survey results indicated that the majority of participants positively assessed the method's ability to visualize data structures and to provide support in the process of building customer understanding based on data. The feedback showed that CDM enables a discussion about data in interdisciplinary teams even without deep data knowledge. Participants emphasized the need to communicate and share an overview of data within a company and positively assessed that the method supports this process as stated by an interviewee: "Due to the increasing amount of data, it is important to get a mutual view on data for marketing and service activities. In this overwhelming topic, the method is able to reduce complexity." The method's output has been evaluated as relevant as it could be utilized by businesses for further communication and planning purposes. A service expert noted: "Start-ups and data-driven companies usually already know their data infrastructure. However, people-centered service industries or even corporations often don't know their digital touchpoints and data. For them, this method is definitely a means to reach a valuable overview of relevant customer data." Feedback of the participants showed that the element of customer context is understandable and helpful to deduct customer understanding. Participants' feedback also pointed towards the distinction of inside-out and outside-in context: participants emphasized the importance of integrating the voice of the customer in the design process and the collection of data that could be provided directly by the customers themselves.

**Ease of Use & Expressiveness:** CDM easily triggers ideas, which is evaluated positively by participants. A participant stated: "Brainstorming was very easy in this task. There has been more output than previously expected." However, the method is not self-descriptive from the beginning, which requires a comprehensive explanation of the method's elements. Additionally, a moderator is required to guide participants through the process. According to the feedback, the method's steps provided a clear view on data. However, the right structuring of collected data on post-its is crucial: if this step is not guided properly, participants can quickly lose the overall perspective. Therefore, a participant suggested: "To offer more structure in the collection of data, an intermediate result in between or a short summary could be helpful." Just like Frisendal [43], participants positively evaluated that the syntax embedded in concept mapping does not resemble any technical language. Finally, it was critically assessed that the deduction of context requires a visual arrangement when collecting context based on customer processes. A participant commented as follows: "If context should be derived from activities, these elements need to be visually arranged to each other."

**Extensibility:** The method's application showed its ability to work on a data overview and to trigger ideas on how to make use of data. However, service design experts reflected that the consideration of customer needs is crucial in the ideation phase: "Even if it can help to analyze data resources and can trigger ideas for data usage, the

method does not identify customer needs. So, qualitative approaches are still highly relevant in the ideation phase.” Testing the combined application of CDM with ideation methods, such as personas, resulted in positive feedback. The use of personas not only supported the view on customer’s processes, it also helped in identifying customer needs. Finally, the method output facilitated the discussion of data integration initiatives for data usage.

## 6. Discussion

### 6.1. Research Contributions

This article presents CDM as a practitioner-oriented method for data-driven service innovation. Businesses must develop a data-centric thinking, but still struggle with the complexity of data and analytics [9, 14, 18]. Corresponding to the call for interdisciplinary work in service design [8, 15, 53], CDM strives to facilitate data understanding on the one hand and customer understanding on the other and is based on CDL as theoretical lens and CM for data visualization. In response to RQ1, CDM takes the customer perspective in the data modeling process to build up data understanding. This perspective is perceived advantageous for several reasons: first, the analysis of customer processes in a service context results in knowledge about the customer’s daily activities and the resulting data structures and sources. The conceptual element of customer context provides the answer to RQ2: it serves as information category to extract additional knowledge based on customer data and serves as entry point for further prescriptive and descriptive analytics. Furthermore, it demonstrates the potential of co-creating customer understanding by obtaining valuable information directly from the customers themselves. CDM pursues the objective to identify customer context attributes from inside-out and outside-in and highlights that the same information often can be acquired from both directions. Service providers must decide wisely in the service design process how to access customer data in order to build up customer understanding and to create the maximum output for customers in their processes. Researchers in DSR (e.g. [55]) outlined that artefacts need to contribute on different levels of abstraction: this work primarily had the purpose of designing CDM as innovation method and demonstrating its application in practice. It is stated, however, that its customer-centered approach also offers contributions on a more abstract level: The research not only transfers the concept of customer context from CDL into a practical setting, but also offers guidance on how to derive context by linking it to the concept of customer processes. Moreover, an important relationship can be described between data understanding, customer understanding and the design of value propositions (see Figure 4). In this context, customer understanding can serve as the foundation for data-driven services in different ways: first, it provides information to improve the understanding of customer needs, e.g. based on their purchase history. Second, this information can be used as a starting point for service personalization and, third, the information represents the value proposition itself. CDM does not aim at replacing

current service design methods for need identification, such as personas. Instead, it offers a useful supplement with a data-driven perspective and positions CDL deeper into data-driven service innovation.

| Data Understanding  |   | Customer Understanding  | Value Propositions |
|---|---|---|--------------------|
| CUSTOMER DATA (PROCESSES)   | CUSTOMER CONTEXT  | IDEATION  |                    |
| Customer visits ( <i>A</i> ) the restaurant ( <i>O</i> ) at noon vs. in the evening ( <i>at</i> ).  | Lunch guest vs. evening guest                                       | <b>1. Personalization</b><br>Lunch menu newsletter  |                    |
| Customer drinks ( <i>A</i> ) a French ( <i>at</i> ) wine ( <i>O</i> ).  | Number of orders of a certain product and deducted wine preferences | <b>2. Understanding Needs</b><br>Identification of certain products consumed at the restaurant (e.g. wine), e.g. for a delivery service |                    |
| Customer orders ( <i>A</i> ) a first course ( <i>O</i> ) as salad ( <i>at</i> ) and a second course ( <i>o</i> ) with meat and French wine ( <i>at</i> ). | Amount of total food & drinks ordered per night                     | <b>3. Data-based Value Proposition</b><br>Personal information service of consumed calories   |                    |

**Figure 4:** Interdependency between Data, Customer Understanding and Value proposition Design

## 6.2 Limitations and Future Method Development

The following limitations must be addressed in the method's design. Despite the explorative evaluation focus, it needs to be stated that a quantitative assessment could not be reached due the low number of cases. To generate quantitative proof of the method's functionality, further applications are necessary. Conditions of the method's applications could not be fully controlled, such as the data knowledge of participants. Evaluation approaches from conceptual modeling techniques can offer guidance here in the future method assessment, e.g. [41]. Furthermore, it must be stated that CDM cannot claim to completely cover the amount of available data and application systems. Instead it pursues the objective to visualize a broad selection of available data resources as the groundwork for creative work with data. CDM could be further developed in different directions: first, additional steps could be included to fully cover the generation of data understanding, e.g. data quality assessment, data completeness, format and the documentation of specific requirements. With regard to data modeling, existing approaches such as ERM might be applied in combination with CDM. However, future research should also investigate requirements that are related in particular to customer data, such as privacy issues or customer identification (e.g. [9, 13, 24]). Second, due to its proximity to conceptual modeling languages, a further development could be a stronger formalization of modeling results, which encompasses data and context. The development of a modeling language could support the communication of results between different stakeholders even more, e.g. in a tool-based format. Domain-specific modeling languages and the development of an ontology are of relevance here as they ensure model quality and integrity and offer a highly formalized graphical notation (c.f. [37, 70]).

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