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Customers Can Do Better! A Case Study of Self-Service Kiosk Technologies at the German Federal Employment Agency

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Abstract. Self-service technologies have been gaining increasing importance in public and private organizations over recent years. One of the predominant responsibilities of the customers in the context of self-service is to enter their data on their own. Self-service for data entry can help organizations to further enhance the efficiency of their processes and to make customer experience smoother. However, as self-service for data entry is intended to be handled without intensive employee assistance, inexperienced data entry can lead to data quality problems. Although academic research has explored several effects of self-service technologies, there is still a lack of research investigating the effect of self-service data entry on data quality. Thus, in an in-depth case study in cooperation with the German Federal Employment Agency we analyzed how customer self-service for data entry affects data quality and found that assisted self-service data entry leads to highest data quality.

Keywords: Self-Service Technology, Data Quality, Case Study Research, German Federal Employment Agency

1 Introduction

Over recent years, organizations have been harnessing the power of new technologies to deliver an increasing number of self-service applications as an integral part of their offerings [1]. Customers and citizens can engage in self-service kiosk technologies at airport and travel kiosks, vending machines, food-ordering kiosks, self-check-ins, health care kiosks, and retail kiosks [2]. Providers perceive self-service technologies as a chance not only to capture greater efficiencies [3] but also as a potential to enable customers as well as citizens to create service outcomes independently of direct involvement of a service firm employee [4], [5]. When customers or citizens engage as "active participants in the organization's work" [6], they are required to take over various responsibilities which formerly resided in the responsibility of the company or

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the government. One of the predominant responsibilities in the context of self-service is that consumers enter their data on their own. Research shows that for companies self-service for data entry is often more time and cost efficient than service by employees as it allows employees to concentrate on more value-generating activities [7]. Forrester Research, for example, points out that self-service technologies can reduce the cost of a service interaction from $35 on the phone to 75 cents online [8].

To fully realize the benefits of self-service data entry, data has to be entered at high quality. However, as self-service data entry is intended to be handled without intensive assistance [7], inexperienced and unsupervised data entry can lead to data quality problems. For example, a competent data entry clerk has an average error rate of 2-4 percent – by contrast, the error rate on the web is 10-15 percent, since members of the public are entering the data [9]. Having high-quality and well-integrated data is hence one of the cornerstones of a successful self-service implementation. It contribute substantially to eliminating operational cost exceeding caused by incomplete and incorrect data, and to enhancing revenue through improved customer targeting and retention [10]. Although in recent years extensive academic work has explored related effects of self-service technologies such as process efficiency and customer satisfaction (e.g. [11-13]), there is still a lack of research investigating the effect of self-service data entry at kiosk systems on data quality. Thus, the aim of this paper is to investigate how self-service for data entry affects data quality and how organizations can improve data quality for existing self-service kiosk technologies. To answer this research question, we conducted an extensive case study in cooperation with the German Federal Employment Agency. The remainder of this paper is structured as follows: In the next section, we first review the existing literature concerning the nature of self-service and related effects. We then describe the research design, followed by the specification of the data collection process. Afterwards, we analyze the data of the German Federal Employment Agency and present our findings. Based on that, we derive implications for research and practice and critically reflect on limitations. Finally, we conclude with a brief summary.

2 Theoretical Background

The transformation of customers from 'passive audiences', who received services and goods, to 'active players' that participate in the organization's work [14] has led to customers engaging in dialogue with the company and taking over various responsibilities which formerly resided in the scope of the company [15]. In that context, researchers have recognized the critical role of technology in the delivery of services [4], [16]. Self-service technologies are defined as "technological interfaces that enable the customers to produce a service independent of direct service employee involvement" [17, p. 50]. To express the notion of self-services, literature contains a number of terms or concepts, such as 'partial employee', 'virtual customer integration', 'co-production' 'mass customization', and 'co-creator'. In the following, we focus on self-service kiosk technologies such as booking terminals or self-service check-ins which are rather present in service environments and which emphasize the technology perspective. Self-service kiosk technologies hence can be described as new operational models that imply new types of customer interactions and customer touch points [18] and it is apparent that they will play an even more important role in service delivery in the future. Customers entering data on their own is one main critical success factor leveraging the potential of self-service kiosk technologies in the future [19].

In response to the increasing role of self-service technologies, researchers have begun to investigate the different effects of self-service technologies from either the organizations' or the customers' perspective. Effects from an organization's point of view include factors such as speed of delivery, precision and customization [20], reduced costs as well as increased productivity and efficiency [12], and improved competitiveness and increased market share [21]. From a customer's point of view, self-services can provide opportunities to enhance satisfaction and loyalty and can lead to positive referrals or word-of-mouth effects [11], [22]. The present paper takes the perspective of an organization that offers self-service technologies to its customers.

In the organizational context, researchers point out the role of data quality [9]. Although quality issues of the customers' contributions in general have been discussed in several conceptual and empirical publications (e.g., [23-25]), the field of data quality has not been investigated in detail so far. Data quality can be defined as the measure of agreement between the data views presented by an information system and that same data in the real-world [26]. It compromises different dimensions such as correctness, completeness, consistency, and currency [27]. Research found that by using self-service the amount of backend data entry work was significantly reduced, which in turn eliminated the need to employ (temporary) data entry clerks [28]. Reid and Caterall state that if customers perform a process less expertly than employees, the quality of the data provided may be compromised [9]. In addition, research has also dealt with the risks of multiple entries of the same data within a multichannel environment. Hence, the transfer of authority to the customer and the related decentralization reduces the chances of a consistent data quality standard being taken [29].

However, beside these first statements confirming that the topic is relevant for research (e. g. [9]), to the best of our knowledge, no study analyses how customer self-service for data entry affects data quality and how organizations can improve data quality at existing self-service kiosk technologies. With datasets growing in size, data quality becomes increasingly important. Prior research emphasizes that insufficient data quality may lead to wrong decisions and high costs [30] and that a high data quality level is needed to perform all kind of decisions and business processes properly [31], [32]. Thus, the following study attempts to fill this research gap by investigating how customer self-service for data entry affects data quality and how organizations can improve data quality at existing self-service kiosk technologies.

3 Research Design

3.1 Case Study Research

To determine how customer self-service for data entry affects data quality, we decided to draw on case study research. We believe that case study research is especially well-suited to our problem for three reasons. First, case study research provides a way to analyze customer self-service kiosk technologies in a natural setting, that means without exerting any control over the process or participants, which allows us to learn about this contemporary phenomenon in depth. Second, since the data quality phenomenon we are investigating cannot be separated from the context of customer self-service for data entry (e.g. there is a difference if employees are available and provide customers with support or not), phenomenon and context are not clearly obvious and we obtain "many more variables of interest than data points" [33, p. 18] and, in the end, more than one result. Third, our analysis relies on multiple sources of evidence as we use both qualitative as well as quantitative data and we have less a priori knowledge than is required to apply other research methods.

The case study research method consists of three stages that structure the research process (see [34]). The first stage, research design, is linked to "the attributes associated with the design of the study" [34, p. 605]. The second stage, data collection, refers to the quality of the data compilation process, including the choice of methods (qualitative and quantitative). Finally, the third stage, data analysis, is concerned with the process description, the techniques, and the modes of separating and grouping the data in order to derive interpretations as a basis for recommendations for action. The remainder of this paper is organized in accordance with these stages.

3.2 Case Setting

We conducted a case study in cooperation with the German Federal Employment Agency (*Bundesagentur für Arbeit*), which is the largest provider of labor market services in Germany with approximately 95,000 employees. The German Federal Employment Agency provides a comprehensive set of services for citizens, companies, and institutions. Its core tasks include placement in vocational training and employment, career counselling, and providing benefits that substitute for employment income, such as unemployment benefits and insolvency payments. These services are provided through a Germany-wide network of 156 employment agencies and about 610 branch offices.

In April 2011, the Federal Employment Agency started a project to investigate the costs and benefits of self-service kiosk technologies for data entry. In this context, to gain deeper insights, the Federal Employment Agency established self-service terminals in the entrance zone of a couple of agencies to support the data entry step in the registration process for unemployed individuals. Allowing or requiring customers to perform parts of a business process themselves is a technique intended to make processes more efficient (by reducing employee labor) and customer oriented (by giving customers a degree of freedom to decide when and how they carry out the process). However, if customers perform the process less expertly than employees, the quality of the data provided may be compromised. In the course of the project, it could be shown that self-service for data entry is more time efficient: the time savings (measured as the effort per customer) compared to the traditional process for data entry involving an agency employee were up to 20%. However, despite these findings, the management as well as the placement advisors were worried that the quality of the data entered by customers themselves would be lower than when entered by an agency employee. The fear was that unemployed individuals would be unable to enter their data as well as an agency employee would, resulting in lower data quality and track-backs to clarify and improve the data sufficiently to make it usable for matching a customer with a job or training opportunity. Agency management was in general agreement that lower data quality would be unacceptable, as high data quality is a key factor in successfully matching unemployed individuals with placement opportunities.

To better understand this “highly exploratory” situation [34, p. 610], we decided to conduct a pilot study at four agencies across Germany (one each in southern, western, eastern and northern Germany) from September to November 2011. In this time period, data was collected on an on-going basis. On average three days a week, a team of two researchers spent “time to develop an intimate understanding of the setting and the phenomenon of interest” [34, p. 611]. This team-based approach allows researchers to obtain a rich set of observations and quantifications, which in turn fosters greater confidence in the results [35].

3.3 Unit of Analysis

The phenomenon under investigation is the process of entering data and the quality of the resulting data set for unemployed individuals. At the Federal Employment Agency, a customer’s profile or data set contains personal information (e. g. name, date of birth, date unemployment started) and contact information (e. g. postal address, email). In addition, the data set records necessary occupational data, for example, information about family status, mobility, and the customer’s personal educational and work-related biography. Finally, the data set contains data on the customer’s job search (e. g. job, location), the customer’s knowledge and capabilities as well as the customer’s self-assessment of his or her personal strengths.

For the process of matching customers successfully with placement opportunities, three categories of information in the data set are especially important for the matching of individuals: First, the CV/résumé of a customer including the customer’s personal educational and work-related biography, second the knowledge and skills of the customer (e.g. language skills), and third the personal strengths a customer has (e.g. goal orientation). Accordingly, these three categories were selected as the focus of the research team’s analysis of data set quality. To be able to analyze the data quality for the three categories depending on different types of data entry processes, the data quality was evaluated for three types of data entry processes in a pilot study. The three different processes for customer data entry are illustrated in Fig. 1.

The first process was data entry by the customer in the employment agency’s entry zone at a self-service terminal without the presence and support of an agency employee (referred to as process 1, unassisted self-service data entry). In that process the customer is asked to go to the self-service terminals, where he or she is led through the self-service application without any help. The second process was for self-service data entry by customers, as in process 1, but with an agency employee available to help (referred to as process 2, assisted self-service data entry). For example, if the customer is not sure about certain CV entries, he or she can ask the assistant for support. The third process (i.e., the data entry process as traditionally executed) comprises data entry by an employee (referred to as process 3, data entry by an employee). After the reception staff member registers the customer as unemployed, the entry zone employee takes the customer's data by means of a conversation and enters the data into the system. The required process result independent of the process is a comprehensive dataset that is required for the next step of matching and placement (typically as a conversation with a placement advisor).

To ensure valid results and create the organizational conditions in the pilot, process 1 was carried out in agencies 1 and 2, and process 2 in agencies 3 and 4. The conventional process to date, process 3, was carried out in all four agencies to provide a basis for comparison. The four agencies were selected in a way that they are comparable with regards to their size and customer structure.

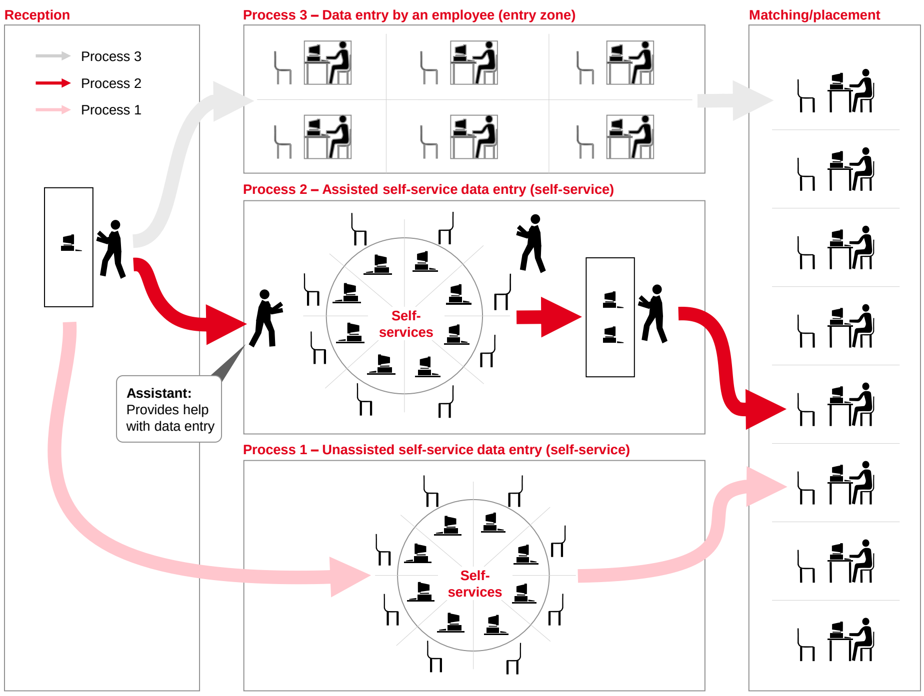

Fig. 1. Three Processes for Data Entry at the German Federal Employment Agency

4 Data Collection

To provide a richer picture of the phenomenon of interest, the relevant literature (e. g. [33], [34]) recommends using different sources of evidence to investigate the unit of analysis. Therefore, to obtain the necessary data, we followed a three-step approach that integrated multiple data collection methods and sources of information (data triangulation) as well as a mix of qualitative and quantitative data.

In a first step, in October 2011, we conducted a survey of n = 110 placement advisors at the four pilot agencies across Germany with a response rate of 83% (n = 91). In these four selected agencies all placement advisors were asked to participate at the survey. The objective was to gain insights into the placement advisors' perspective on the quality of the data sets for the three different processes (see Fig. 1). The survey consists of a six-point Likert scale and includes closed as well as open questions. As the placement advisors have to work with the entered data and are responsible for the placement of their customers (including monthly targets), it seemed critical to have them assess the data quality of the different data sets. The key question in the survey was: "How would you rate the quality of the customer-profile data in terms of completeness for matching purposes for customers who have undergone the following process?" To get a comprehensive picture beyond the survey data, we decided to conduct ten semi-structured interviews with placement advisors from all four agencies, to get insights into people's daily life. The interviewees were selected from the local management with respect to the criterion of high-performing placement advisors. The interviews had an average length of 30 minutes and were conducted in October 2011 according to an interview guide. We conducted the interviews in person and recorded, transcribed and translated them from German into English [36]. Please note that the interviews only served to give context and to confirm assumptions and to reflect on findings that were made based on the survey.

In a second step, our objective was to determine the data quality of the data sets (consisting of CV/résumé, knowledge and skills, and personal strengths) of unemployed persons (data triangulation). To that end, we collected n = 428 customer data sets at the four agencies for the three processes by randomly drawing them from the Agency's IT system VerBIS. The sample size of n = 428 equals about 5% of the total population (n = 9,018) that passed through one of the processes described above in an average month between September and November 2011. The selected data sets were printed as PDF documents for data analysis. The results of the analysis of the different data sources are presented in the following section.

5 Data Analysis and Results

5.1 Elucidation of the Data Analysis Process

With our guidance, three experts from the headquarter (> 10 years of professional experience; formerly placement advisors, not dependent to the pilot agencies) evaluated the three categories – CV/résumé, knowledge and skills, and personal strengths – of the 428 data sets with respect to data quality. Their evaluation was based on agreed-upon criteria (discussed in the next section) and conducted by the three experts independently of each other to avoid subjective distortions and to increase the reliability of the results. As practiced by Romm and Pliskin [37], one researcher was involved in all data analysis activities to ensure objectivity. When evaluation issues emerged during the analysis, we decided on the best-fitting interpretation through team discussion. The reliability of agreement between the experts was measured with

Fleiss' Kappa [38]. We observed a value for Fleiss' Kappa of nearly 88% which reflects an "almost perfect agreement" between the experts [39].

5.2 Measures for the Analysis of the Data Sets

The data quality level of a data set is measured by the completeness of the three categories CV/résumé, knowledge and skills, and personal strengths. Completeness as a data quality dimension represents "the extent to which data are of sufficient breadth, depth, and scope for the task at hand" [40]. We decided to focus on the data quality dimension completeness for two major reasons. On the one hand, completeness is one of the key dimensions of data quality and its measurement does – in contrast to other data quality dimensions like correctness – not necessarily require a so-called real world test [41]. Indeed, a real world test in terms of a direct comparison of the data to their corresponding real world counterparts is usually very time-consuming and cost-intensive or not at all practicable (e.g. for large data sets) (cf. [42]). On the other hand, complete data are paramount in the context of placement of unemployed individuals as complete data with respect to the three categories is an indispensable requirement for successful matching within the Federal Employment Agency's JOBBÖRSE. The Federal Employment Agency attributes the data quality dimension completeness the highest relevance for a successful matching of an unemployed person.

We measured the completeness of each of the three categories on a three-point Likert scale (1=low data quality; 3=high data quality). This procedure was discussed in advance with several experienced placement advisors in each agency who checked the scale as well as the guidance for each scale item. For the category CV/résumé, for example, they concluded that a result would have "low" quality if the CV/résumé contains gaps or if the customer's occupational training and qualifications have obviously not been entered. Furthermore, they unanimously agreed that a CV/résumé with "high" data quality must cover the past seven years.

5.3 Research Findings

Assessment of the Data Quality Level based on the Survey and the Interviews. On the basis of the results of the survey of the placement advisors, we found that the advisors give the highest rating for data quality to process 3 (data entry by an employee) (average data quality level = 4.3) followed by process 2 (assisted self-service data entry) (average data quality level = 3.2) (see Fig. 2). Regarding process 1 (unassisted self-service data entry), the results show that the level of data quality receives the worst rating. Fig. 2 summarizes the results. The ANOVA as well as the pairwise post-hoc comparisons using the Tukey Honest Significant Differences (HSD) test indicate significant differences ($p<0.01$) between the mean scores of the three processes.

The evaluation of the qualitative comments in the survey yields some observations concerning the placement advisors point of view. Various statements can be found that indicate that the data quality in the case of assisted self-service data entry is worse, as "the customer is not aware of how important it is for placement to enter complete data" (survey comment). In addition, the analysis of the interview notes lead to the conclusion that self-service data entry is associated with anxieties that are not directly related to data quality, but nevertheless influence the ratings. For example, seven out of the ten placement advisors interviewed in depth mention that they are of the opinion that “a positive evaluation of the self-service data entry would lead to job reductions” (statement by one placement advisor). Furthermore, eight out of the ten placement advisors are of the opinion that unemployed individuals (especially older individuals) are “overtaxed by the process of correct and complete data entry” or “unemployed individuals can carry out this [process] far more poorly than the employees” (statements by two placement advisors).

	Average data quality level (1=very bad; 6=very good)		
Assessment data quality (*n*=91)	**Process 1** (Unassisted self-service data entry)	**Process 2** (Assisted self-service data entry)	**Process 3** (Data entry by an employee)
How would you rate the quality of the customer-profile[1] data in terms of completeness for matching purposes for customers who have undergone the following process?	2.1	3.2	4.3

1 CV/résumé, Knowledge and skills, Personal strengths

Fig. 2. Assessment of the Data Quality Level With Respect to the Three Different Processes

Assessment of the Data Quality Level based on the Data Sets. On the basis of the 428 data sets and their evaluation, we found that for the category CV/résumé process 3 (data entry by an employee) is the process with the highest data quality (average data quality level = 2.6). First and foremost, the results make clear that – for the category knowledge and skills – the data quality for process 2 (assisted self-service data entry) is the highest (average data quality level = 2.5). This means that the average data quality level for the category knowledge and skills in process 2 is around 39 percent higher than for process 1 and 25 percent higher than for process 3. For the third category, personal strengths, the data quality is also the highest for process 2 (assisted self-service data entry), with an average data quality level of 2.6.

Assuming that all three categories are equally important for the placement of the Federal Employment Agency’s customers (that was jointly decided with the experts, the local management, and the headquarter), we aggregated the single data quality levels to an overall level. The results indicate that for the three categories analyzed, data quality is the highest for process 2 (assisted self-service data entry) (average data quality level = 2.5). Fig. 3 summarizes the results. The ANOVA reveals significant differences ($p<0.01$) between the mean scores for the overall quality level of three processes. In addition, post-hoc comparisons indicate significant differences ($p<0.01$) between the mean score of process 2 (assisted self-service data entry) and the other processes ($p<0.01$) while the mean scores of process 1 (self-service data entry) and process 3 (data entry by an employee) do not significantly differ.

Process (n=428)	Average data quality level (1=very low; 3=very high) CV/résumé	Knowledge & skills	Personal strengths	Level overall
Process 1 (Self-service data entry)	2.4	1.8	1.9	2.0
Process 2 (Assisted self-service data entry)	2.5	2.5	2.6	2.5
Process 3 (Data entry by an employee)	2.6	2.0	1.9	2.2

Fig. 3. Average Data Quality Levels for the Three Different Processes

Analysis with Respect to the Customers' Educational Background and Age. To get deeper insights, we analyzed the average data quality level for the three different processes with respect to the customers' educational background and age. Based on the German education system, we distinguished the three educational background categories "low" (no educational achievement or lower secondary education), "middle" (certificate of secondary education), and "high" (higher education entrance qualification). For 52 of the 428 customers no data regarding educational background was available (n=376). We found that our previous results also hold for each of these educational categories (Fig. 4). It is remarkable that for the assisted self-service entry the data quality level significantly ($p<0.01$) differs with respect to the customers' educational background, a fact that cannot be observed for the other process alternatives.

Process (n=376)	Average data quality level with respect to education background (1=very low; 3=very high) "Low" education	"Middle" education	"High" education	Overall
Process 1 (Self-service data entry)	2.1	2.2	2.1	2.1
Process 2 (Assisted self-service data entry)	2.3	2.7	2.9	2.6
Process 3 (Data entry by an employee)	2.2	2.4	2.2	2.3

Fig. 4. Average Data Quality Levels for the Three Different Processes Considering Customers' Educational Background

The Federal Employment Agency differentiates the age groups "under 25 years old" (young), "25 to 49 years old" (middle), and "50 years and older" (old). Our analyses (cf. Fig. 5) show that for each of these age groups data quality again is the highest for process 2 (assisted self-service data entry) and the mean scores for the data quality level of three processes significantly differ ($p<0.05$). In this context, our results underpin that self-service kiosk technologies should not be reserved for young people and digital natives only. In our study, we did indeed observe the highest average data quality level of 2.6 for the customers of the age group “50 years or older”. It should, however, be noted that especially with respect to this age group the average data quality level is subject to a massive and significant ($p<0.05$) decline if no agency employees are available to provide assistance (average data quality level of 1.8).

	Average data quality level with respect to customers' age (1=very low; 3=very high)			
Process (*n*=428)	**"Young"**	**"Middle"**	**"Old"**	**Overall**
Process 1 (Self-service data entry)	1.9	2.1	1.8	2.0
Process 2 (Assisted self-service data entry)	2.4	2.6	2.6	2.5
Process 3 (Data entry by an employee)	2.1	2.2	2.4	2.2

Fig. 5. Average Data Quality Levels for the Different Processes Considering Customers’ Age

6 Implications and Limitations

This study investigated how customer self-service for data entry affects data quality and how organizations can improve data quality at existing self-service kiosk technologies. One notable finding of the case study in cooperation with the German Federal Employment Agency is that the data quality level is the highest in case of an assisted data entry by the customer at a self-service terminal – this holds true over all customers’ educational and age categories. Therefore, we can conclude that organizations can improve data quality from existing self-service kiosk technologies by providing assistance rather than switching from self-service to personal services. The results of this study complement existing knowledge and contribute to a better understanding and profound conclusions which self-service to apply when data quality matters.

As findings of data quality research indicate, a high data quality level is a prerequisite for good decision making, improved customer targeting and retention, and successful self-service implementation, further studies should be conducted to investigate how customers can be motivated, stimulated, or rewarded to enter their data on a high quality level when using self-service technologies. In that context, prior research analyzing motivations for using self-service [4], could be extended by integrating factors such as assistance by an agency employee that may lead to better data quality. Thereby the influence of the skills of the assistant could be examined further.

Additionally, as current research has raised the question how new operational models involving self-service have to be designed to create a high customer adoption [18], [19], future research should consider the appropriate design of self-service to ensure high data quality. As research findings indicate citizens prefer to use more media in parallel for their contacts with governments in the future [43], this public service delivery by multi-channel requires detailed evaluations of whether self-services should be applied, whether assistance should be provided and which data quality level should be targeted. Furthermore, negative side-effects such as over-proportional need of assistance could occur and hence have to be considered. There exist first approaches that develop quantitative economic decision models to assess self-service data entry effectiveness and efficiency (e.g. [44]), but do not integrate the data quality dimension so far. Thus, future research should integrate existing data quality metrics (e.g. [32]) in economic models for self-service implementation.

As decision makers rarely take the effects of data quality into account when deciding on the implementation of self-service for data entry, our study has several implications for practice. First, as our research indicates an assisted self-service process for data entry at existing self-service kiosk technologies can be a viable alternative to the traditional data entry by an employee and to the implementation of unassisted self-service. Second, as poor quality can lead to wrong decisions resulting in high costs [45], our study helped revealing one of the major cost factors decision makers should consider when implementing self-service. Third, when deciding on the application of self-service, the new roles, the required skills and learning processes for both, employees and customers have to be considered [46]. Finally, in the Federal Employment Agency case, it proved very helpful to conduct a pilot study and apply a multi-method approach including qualitative and quantitative analyses in order to get deeper insights in the different self-service processes. Thus, we encourage practice to conduct preliminary pilot studies incorporating different sources of evidence.

Nevertheless, there are several limitations in this study. First, we only conducted a single case study in one country. However, the German Federal Employment Agency is one of the largest public sector institutions in Europe. Thus, we can assume that our results have certain significance. Nevertheless, future research should consider further cases in other industries and countries to validate the results. Second, in the case study conducted we focused on one possibility of data entry in self-service. As providing data at a kiosk could be different from performing data entry online or via social media, further research should analyze similarities and differences between different channels. This is of special importance as social media is currently already influencing self-service adoption in the public sector [47]. Third, we only conducted surveys with the placement advisors and did not include the customers' point of view. As self-service require both, customers' and organizations' interaction, future research could analyze why self-service may harm data quality (from the customers' point of view) to understand why quality problems may exist. Finally, in our analysis we focused on completeness which is indeed one of the most important data quality dimensions. Nevertheless, further research should also include other important data quality dimensions like correctness, currency, and consistency (cf. e.g. [41]).

7 Conclusion

Self-service kiosk technologies for data entry seems a promising means to integrate customers into the value chain and make business processes more efficient with respect to working time and costs. However, many companies and public institutions like the German Federal Employment Agency fear potential data quality problems, if data is entered by customers themselves, and therefore still hesitate to adapt their business processes to make use of customer self-service kiosk technologies. To shed light on this contemporary phenomenon, we decided to draw on case study research (cf. [33]) to investigate in depth and within a real-life context how customer self-service for data entry affects data quality and how organizations can improve data quality at existing self-service kiosk technologies. Our main results are twofold. On the one hand, the survey and the interviews reveal that employees are somehow skeptical about customer self-service kiosk technologies for data entry and point out negative effects with respect to data quality (to a certain extent this skepticism seems to stem from anxieties around possible job reductions due to the growing use of self-service technologies). On the other hand, analyses of the 428 data sets resulting from the data entry step show that data quality is the highest (even higher compared to data entry by an employee) in case of an assisted data entry by the customer at a self-service terminal with agency employees providing help and answering questions. It is remarkable that this result holds over all customers' educational and age categories, a fact that indicates that self-service kiosk technologies should not be reserved for young people and digital natives only. Overall, our research provides first interesting insights on how customer self-service for data entry affects data quality. Beyond that, we hope that it will open doors for further research in this exciting research area.

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