Business Impacts of Data Analytics in the Service Sector: A Systematic Literature Review

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Abstract: The service sector is one of the industries that is most affected by digital technology and data analytics. Despite a large body of literature on the effects of various data analytics techniques, a comprehensive review of academic insights into impacts of data analytics in the service sector is missing. The goal of this paper is a systematic literature review of impacts that data analytics techniques exert on the performance of service provision. A sample of 70 scholarly articles has been identified and analyzed. A majority of the analyzed articles addresses data analytics in general, big data analytics techniques, or artificial intelligence, whereas a lower number of studies investigates the impacts of concrete data analytics techniques. The impacts of data analytics can be categorized into factors that relate to customer responses, management and decision-making, and long-term indirect effects on competitiveness and monetary impacts. The findings further show that data analytics based on big data analytics techniques yields different outcomes than analytics approaches that are based on artificial intelligence.

1 INTRODUCTION

Data analytics has gained significant importance with an increasing availability of large volume data and data analysis capabilities. This development has facilitated the emergence of new business processes (e.g., industry 4.0), the creation of new business models, such as value co-creation models, and the transformation of entire industries, referred to as digital business transformation (Akter et al., 2022). Digital business strategies and organizational capabilities are key drivers of digital transformation (Nadeem et al., 2018).

Digitalization and data analytics have the potential to transform any industry and one of the most affected ones is the service sector. This industry has experienced foundational transformations, which occur on multiple levels. Services contain numerous interactions with customers that can result in customer data. This allows real-time responses to customer demand, behavior, and events in service provision. Data analytics provides insights into customer behavior that go beyond traditional insights from transaction data and empirical data collection (Kumar et al., 2013). Many components of service provision can be digitized so that besides an enhanced data-driven exchange of information between service provider and customer, data analytics enables the application of innovative technologies with enhanced interaction with the customer, such as robotics and chatbots (Sun & Wang, 2022). Illustrative examples are fintechs, a business model that has transformed the financial services sector and led to a new category of service providers with altered ways of delivering services (Werth et al., 2023), or peer-to-peer platforms such as Airbnb in the hospitality sector (K. H. Lee & Kim, 2019).

Evidence of the transformative potentials of data analytics in different economic sectors is manifold and growing fast. The diversity of applications has resulted in a multitudinous array of impacts in various ways which makes it difficult to obtain a comprehensive overview of the state of the art of research on impacts of data analytics on business. Scholars have addressed this need by providing literature reviews in an array of industries, such as manufacturing (Getachew et al., 2024), supply chain management (Darbanian et al., 2024), healthcare engineering (Salazar-Reyna et al., 2022), or innovation research (Natividade Joergensen & Zaggl,

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2024). However, to date no systematic literature review within the service sector could be identified. Against this background, the objective of this study is to provide a first systematic review of scholarly research on concrete effects of data analytics techniques in the service sector. We seek in particular to address the following questions:

What impacts of various advanced data analytics techniques in the service sector are identified in scholarly literature?

What are variations of effects by data analytics techniques and industries within the service sector?

The insights obtained from this systematic review allow a comprehensive overview of the state of the art of scholarly research on an industry that is particularly affected by data analytics in various ways. It helps scholars to develop a research agenda for an enhanced investigation of the potentials of data analytics techniques in different industries within the service sector and thus to get a better understanding of impacts of data analytics on customer experience and behavior, operational management, and long-term strategic benefits for service providers.

2 DATA ANALYTICS TECHNIQUES

Data analytics is the capability of obtaining insights from data by carrying out different, primarily quantitative analysis methods, such as statistics and mathematics, econometrics, optimizations, simulations, classifications, or other methodologies to improve decision-making (G. Wang et al., 2016). It thus describes a set of different analysis techniques and methodologies. From a data point of view, contemporary data analytics is usually based on big data, whereby analysis methods and algorithms primarily utilize datasets that exceed the capacity of traditional databases. Big data analytics is characterized by five features that distinguish big data from conventional databases: Volume refers to the large amount of data, variety denotes a high number of different types and formats of data, velocity stresses the high speed at which data is retrieved as well as analyzed (often in real-time), and veracity describes the correctness and thus trustworthiness of analyzed data (Akter et al., 2022). Value refers to the potentials of big data analytics to obtain insights that can unlock benefits to an organization such as customer centricity or innovative product or service offerings.

From an analytics process viewpoint, contemporary data analytics increasingly relies on artificial intelligence (AI) and is intertwined with big data analytics (Duan et al., 2019). While big data analytics does not necessarily require AI tools for analysis, AI is typically reliant on large amounts of data (Akter et al., 2022). AI combines different computing technologies to facilitate rational decision-making in complex situations and contexts (Duan et al., 2019). AI capabilities require a system to be able to conduct natural language processing, retrieve and process data from large databases, apply mathematical theories, carry out automatic programming, and solve critical problems (Nilsson, 2014). An important prerequisite is the availability of massive amounts of data that permit an AI system to learn from the data in one of two ways, i.e., machine learning or deep learning (Akter et al., 2022).

Machine learning consists of several types: Supervised learning is based on providing labeled data that is used to train the system to predict outcomes resulting from these data. Unsupervised learning is based on unlabeled and unstructured data where no target variable is defined (Syam & Sharma, 2018). Another machine learning type is reinforcement learning. It is based on trial and error, whereby a positive response to an outcome reinforces their connection (Rolf et al., 2023). Reinforcement learning has shown to provide superior outcomes particular in collaborative conditions where computing devices are linked (Udayakumar & Ramamoorthy, 2023). Deep learning processes data in its raw form, which permits advanced analytics such as speech recognition, image recognition, object detection, and others based on unsupervised learning. Artificial neural networks are an application of deep learning where analytics takes place on multiple layers. On each layer, the input is transformed in a non-linear way and represented as an output whereby layers are connected via nodes (Lemley et al., 2017).

3 METHODOLOGY

To understand the role of data analytics in the service sector, a systematic literature review has been conducted. To capture a significant body of literature, we conducted a search within the electronic databases EBSCO Host and Scopus (Diaz Martinez et al., 2024) and further expanded the search through forward and backward cross-referencing. The search string was defined on the basis of literature on data analytics and includes the following terms: ("data analytics" OR “machine learning” OR “artificial intelligence” OR AI OR “deep learning” OR “neural network”) AND ("service sector” OR “service industry”). To ensure

that the search results are limited only to high-quality peer-reviewed journal articles, we only included publications in journals, which are ranked in the first or second quartile of the Scimago ranking. Only articles published 2014 or later in English language were included in the search.

This literature search, conducted in April 2024, identified 259 articles after the elimination of duplicates. The titles, abstracts, and full papers have then been reviewed to determine their relevance for the study in terms of the inclusion criteria below. To be included in the final literature selection,

- articles have to contain an empirical analysis. This is not limited to specific methods. Hence, besides the use of various data analytics and AI for data analysis itself, also papers that apply other analysis methods of empirical data about data analytics (e.g., surveys, semi-structured interviews) are included in the sample. On the other hand, literature reviews or conceptual studies were not included in the sample.
- articles have to refer to data analytics, either as a specific data analytics method or data analytics in general as an independent variable.
- the research context of articles has to be situated in the service sector or at least be associated with service provision (e.g., services in the context of manufacturing).

This rigorous process led to the final inclusion of 70 articles including cross-referenced articles that met the above-mentioned inclusion criteria, but were not found in the initial keyword search. The articles selected for the analysis were structured in a concept matrix (Webster & Watson, 2002) on the basis of the Theories, Contexts, and Methodology (TCM) framework (Paul et al., 2017). First, we extracted descriptive information from each article based on each criterion. We recorded all mentioned theories, collected information of the concrete service sector (e.g., finance, hospitality) and geographical scope, where applicable, and listed all mentioned methodologies. Next, we inductively coded the concrete attributes and types of data analytics methods and the respective dependent variables, i.e., effects of data analytics discussed in the articles. The specification of data analytics methods is heterogenous in the investigated articles. Most articles refer to big data analytics, artificial intelligence, and data analytics in general. Coding of the effects of data analytics resulted in 43 single variables that were further grouped into 14 categories which belong to two main areas (impacts on interactions with customers and internal effects on the organization).

4 RESULTS

4.1 Descriptive Analysis

Out of 70 identified articles, 21 primarily relate to big data analytics in general, 18 to AI in general, 7 to machine learning, 16 to further single methods such as regression-based models, neural networks, or k-nearest neighbors, and 8 to data analytics in general, without specifying concrete applications or methods.

The service industry context is discussed as follows: 16 articles refer to the finance sector (banks, fintechs, insurances, other financial service providers). 9 articles refer to the hospitality sector (hotels and other touristic services), 4 articles deal with healthcare, another 4 with supply chain management (SCM), 3 with manufacturing, and 10 with other areas (public sector IT services, smart city infrastructure, real estate, foodservice, consulting, direct marketing services, IT Management, telecommunications, aviation, and small-and medium-sized enterprises). The majority of articles (24) addresses the service sector in general, without referring to a specific industry.

4.2 Categories of Data Analytics Impacts

The open coding of impacts of data analytics yields 14 groups of effects of data analytics in the service sector. These groups are the following:

- Decision-making (N=19): Positive effects on decision-making in the organization, i.e., better decision outcome or decision-making process.
- Service offerings (N=26): Positive effects on the service provision, such as new service offerings, improvement of service quality, or enhanced customer service.
- Management/governance (N=26): Positive impacts on specific areas in management and/or governance, such as risk management, intra-organizational processes, or planning. It also includes higher managerial skills and competencies, such as data management, compliance, or resource allocation.
- Customer management (N=15): Positive impacts including improved ways of handling customer interactions, the process of providing service offerings to customers, and/or obtaining customer insights.
- Personalization of services (N=12): More services tailored to individual customers.

- Customer response (N=28): Impacts of data analytics on customer response, such as improved relationships of customers with the company, improved customer experience, and customer satisfaction.
- Innovation (N=5): Positive impacts on the organization's innovativeness, e.g., novel offerings, innovation management process.
- Monetary impacts (N=13): Positive impacts on the financial well-being of the organization, i.e., profitability, sales, and reduction of costs. These cost reductions are mainly driven by improvements of primary business activities, such as efficiency gains in operations (see below) and enhanced customer interactions.
- Efficiency (N=26): Positive impacts on service operations efficiency, particularly by general efficiency gains in service provision and efficiency increase in single business domains such as audits or medical treatments.
- Competitive advantage (N=10): Positive impacts on the organization's competitiveness by yielding competitive advantages.
- Single business administration functions (N= 11): Human resource management (8 articles), supply chain management (2), marketing (1).
- Corporate social responsibility (CSR; N=7): Positive or negative social and/or ethical implications of data analytics for issues such as privacy, individual and social welfare, or impacts on the environment.
- Data value (N=4): Positive impacts on the organization's ability to enhance the value of existing data, such as being able to identify fake reviews or improve predicting capabilities.
- Transparency (N=3): Positive impacts on the availability and/or accessibility of data and processes that are supported by data analytics.

4.3 In-Depth Analysis of Data Analytics Impacts

In the following, the analysis results are presented in detail. Tables 1 to 5 show the distribution of identified impacts of big data analytics, AI, machine learning, specific data analytics techniques, and data analytics in general on the identified 14 factors in each article. For the sake of readability, the single business functions and the categories of CSR, data value, and transparency are summarized in one column, respectively.

Overall, the most frequently reported impact of data analytics across all types is customer response

Table 1: Impacts of big data analytics in the service sector.

Context	Decision-making	Service offerings	Management/ governance	Customer management	Service pe-sonalization	Customer response	Innovation	Monetary impacts	Efficiency	Competitive advantage	Business functions/ further areas	Reference
Finance	X	X	X									(Hajiheydari et al., 2021)
		X		X							CSR	(Arthur & Owen, 2019)
	X	X				X		X	X			(Bratasanu, 2017)
		X				X	X					(Gozman et al., 2018)
				X								(Vo et al., 2021)
		X	X			X			X	X		(Herrmann & Masawi, 2022)
SCM	X								X	X	SCM	(Khan, 2019)
			X								SCM	(Gocer & Sener, 2022)
Manufacturing			X		X				X			(Lu & Xu, 2019)
	X	X			X	X			X	X	HR	(Shukla et al., 2019)
	X	X					X					(Niebel et al., 2019)
Public sector	X	X										(Choi et al., 2018)
Service sector in general					X			X	X			(Cristescu et al., 2023)
	X			X	X	X	X					(Shirazi & Mohammadi, 2019)
	X		X	X						X	HR	(Parmar & Vidyasagar, 2023)
						X						(Boldosova, 2020)
	X		X					X	X			(Bumblauskas et al., 2017)
	X	X				X			X			(Akter et al., 2019)
		X				X			X			(Noble & Mende, 2023)
		X		X	X	X		X	X			(Bezuidenhout et al., 2023)
											CSR	(Belanche et al., 2024)

Table 2: Impacts of artificial intelligence in the service sector.

Context	Decision-making	Service offerings	Management/ governance	Customer management	Service personalization	Customer response	Innovation	Monetary impacts	Efficiency	Competitive advantage	Business functions/ further areas	Reference
Finance		X	X			X						(Mogaji & Nguyen, 2021)
				X	X				X			(Mogaji & Nguyen, 2022)
											CSR	(Lui & Lamb, 2018)
Hospitality			X					X				(Neuhofer et al., 2021)
						X		X				(Nam et al., 2021)
		X				X						(Li et al., 2022)
		X			X				X			(Buhalis et al., 2019)
						X				X	HR, CSR	(Kandampully et al., 2022)
SCM			X		X			X	X			(Khalifa et al., 2021)
Healthcare	X	X	X									(Sood et al., 2022)
											HR, CSR	(Cavanagh et al., 2022)
Smart city			X								CSR	(Muhammad et al., 2019)
Service sector in general											HR	(Gu et al., 2022)
			X			X			X			(Ameen et al., 2023)
		X				X			X			(Flavian & Casalo, 2021)
			X					X	X	X	HR	(Rana et al., 2022)
						X					CSR	(T. Kim et al., 2022)
		X			X	X		X	X			(Wirtz et al., 2018)

(39% of the analyzed articles), followed by service offerings, management, and efficiency gains (36% of articles each). The least frequently reported impacts of data analytics are innovation (7% of articles), competitive advantages (14%), personalization of services (17%), and monetary effects (18%). Improved decision-making (26% of articles) and customer management (21%) range in the middle. The analysis of benefits reported by type of data analytics tools reveals significant differences. In the context of big data analytics (Table 1), the most frequently reported impacts are the improvement of service offerings, decision-making, efficiency gains, and customer response. Most insights have been obtained in studies that refer to the service industry in general. In terms of industry sectors, the finance sector particularly benefits from improvements that can be experienced by customers (service offerings, customer response), whereas improvements in decision-making and efficiency gains have been reported less frequently there. When it comes to impacts of AI (Table 2), positive effects are particularly reported on customer response, efficiency, management, and service offerings. The most frequently investigated single service sector in this category is the hospitality sector, where reported effects are rather evenly distributed and show a similar pattern as studies that do not specifically relate to a particular service sector.

Studies that focus on machine learning are smaller in numbers (Table 3), yet report noteworthy effects particularly on efficiency, compared to evenly distributed impacts on decision-making, management, customer response, and monetary benefits. In this context, studies that were done in the hospitality sector identify a lower number of positive impacts than in other or general service sectors.

Articles that investigate specific data analytics tools (Table 4) primarily report positive impacts on management, whereas other types of impacts are identified less frequently than in other data analytics contexts. In addition, articles in the finance sector report more positive impacts on customer management and management/governance, whereas positive impacts on efficiency and innovation are found in other industries.

Finally, the studies that do not differentiate between concrete types of data analytics (Table 5) predominantly report impacts on the service offering and management, yet less on decision-making. In this context, one study done in the foodservice industry reports most positive impacts, whereas the other or general service sectors are shown to display evenly distributed positive effects across the categories.

Table 3: Impacts of machine learning in the service sector.

Context	Decision-making	Service offerings	Management/governance	Customer management	Service personalization	Customer response	Innovation	Monetary impacts	Efficiency	Competitive advantage	Business functions/ Further areas	Reference
Hospitality											Data	(M. Lee et al., 2022)
		X										(Kalnaovakul & Promsivapallop, 2023)
SCM						X					Transparency	(Tian et al., 2022)
Real estate				X				X	X	X		(McGrath et al., 2019/20)
Service sector in general	X		X					X	X			(Udayakumar & Ramamoorthy, 2023)
	X			X		X			X			(C.-H. Wang & Lien, 2019)
			X								Transparency	(Titl et al., 2024)

Table 4: Impacts of specific data analytics methods in the service sector.

Context	Data analytics method	Decision-making	Service offerings	Management/governance	Customer management	Service personalization	Customer response	Innovation	Monetary impacts	Efficiency	Competitive advantage	Business functions/ Further areas	Reference
Finance	Vector representation	X					X					Marketing	(Oh et al., 2023)
	Lasso log regression, decision tree, neural network			X								Data	(Ahn, 2023)
	Neural network, k-nearest neighbors			X			X						(Holopainen & Sarlin, 2017)
	k-nearest neighbors				X								(Rjoub et al., 2023)
	Neural network, classification				X							Data	(Ogwueleka et al., 2012)
	Neural network			X	X								(Sharma et al., 2015)
Hospitality	Text analytics			X			X						(Mariani & Borghi, 2023)
	Neural network							X					(Peng & Lai, 2014)
Marketing	Hayes process model		X		X				X				(Abbu & Gopalakrishna, 2021)
IT	Software-mediated Process Assessment	X	X							X		Transparency	(Shrestha et al., 2016)
Telecom	Neuro-fuzzy techniques				X								(Abbasimehr et al., 2012)
Transport	Neural network			X									(Zhao et al., 2019)
Service sector in general	Data visualization	X		X						X			(Tang et al., 2017)
	IoT-based analytics		X			X	X			X	X		(Karttunen et al., 2023)
	Association Rule Mining, Data Envelopment Analysis	X		X				X				Data	(C. Kim, 2017)
	Data Envelopment Analysis	X											(Zhou & Zhan, 2021)

5 DISCUSSION

This study provides first insights into the role of data analytics in the service sector. While this scope is rather broad, it allows to capture a wide range of publications and resulting insights into methodological approaches and specific service sectors that are addressed in research. The identified categories of data analytics impacts in the service sector show two mainly affected areas in business. The first one is impacts on interactions with customers. These factors are either direct perceptions

Table 5: Impacts of general data analytics approaches in the service sector.

Context	Decision-making	Service offerings	Management/ governance	Customer management	Service personalization	Customer response	Innovation	Monetary impacts	Efficiency	Competitive advantage	Business functions/ further areas	Reference
Finance						X		X	X			(Gul et al., 2024)
Healthcare		X	X									(Choroszewicz & Alastalo, 2023)
		X							X			(Dai & Shi, 2021)
Foodservice		X	X	X	X	X				X	HR	(Voipio et al., 2023)
Consulting		X	X									(Pemer, 2021)
SME				X	X				X	X		(Akpan et al., 2022)
Service sector in general	X		X			X					HR	(Cao et al., 2015)
		X										(Belanche et al., 2019)

and behaviors of customers (customer response category) or can be directly perceived by customers (service offerings, service personalization, and customer management). The second area consists of impacts that affect the organization internally. Hereby, impacts are observable on an operational (efficiency) level, in a management context (management/governance, decision-making) or on a long-term strategic level that affects the entire organization (innovation, competitive advantages, monetary impacts).

Across all data analytics techniques that were investigated, the most frequently reported impacts are in the area of customer interactions and thus affect service provision in a way that can be experienced by customers. Especially articles on big data analytics, machine learning, and specific analytics methods show that data analytics positively affects customer satisfaction, relationship, retention and loyalty, thus supporting the notion of data-driven customer relationship management (Jabado & Jallouli, 2024). This connection is strengthened by the large number of articles that investigate customer response together with improved service offerings. The picture is different in the context of AI where various customer experiences are the dominant variable being impacted by data analytics. This is particularly due to the altered application context of AI which is often characterized by direct customer interaction such as robotics (T. Kim et al., 2022) or chatbots (Lui & Lamb, 2018). This pattern is consistent across the different industries within the service sector. A more detailed review of impacts on service offerings shows that data analytics particularly improves service quality as well as the way traditional services are transformed. Examples of service quality improvement are a higher degree of standardized high-quality service provision (Wirtz et al., 2023), superior financial advice of customers (Herrmann & Masawi, 2022), or enhanced patient care in the healthcare sector (Dai & Shi, 2021). Customer management which also results in an improved interaction between service providers and customers is primarily influenced by big data analytics, machine learning, and various specific data analytics methods, yet less frequently reported in the context of AI. In contrast, service personalization is associated with all kinds of data analytics techniques, yet reported in fewer studies of the sample.

Internally relevant impacts are most frequently reported in the context of efficiency and management. Efficiency gains are largely found on an operational level in all investigated service industries. Data analytics particularly contributes to improvements of operational processes, reduction of manual work, and process control, which are enabled through innovation (Conti et al., 2024). When it comes to positive effects on management, articles are highlighting different areas that are relevant in the respective industries, such as investment management in the finance sector (Herrmann & Masawi, 2022), production process reengineering (Lu & Xu, 2019), compliance with quality standards in supply chain management (Khalifa et al., 2021), or pandemic management in healthcare (Sood et al., 2022). A notable difference by data analytics techniques can be found in the context of decision-making where many articles report positive impacts of big data analytics and some specific analytics methods, whereas AI is addressed in only one article in this respect. This supports the notion that at present, AI tools are primarily effective in operational contexts (Hasan et al., 2024), whereas managerial decision is preferably data-driven (Desgourdes & Ram, 2024). The improvement of decision-making through AI systems has been shown in the context of

clinical decision-making (Tikhomirov et al., 2024), however appears to be challenged at present in a managerial context due to the requirement of complementary human leadership skills (Duică et al., 2024).

Interestingly, the number of articles that report far-reaching, long-term strategic impacts of data analytics is comparatively low. Out of 70 articles, only 13 show positive monetary impacts such as profit increase or cost reduction, 10 report impacts on competitive advantage, and 5 on innovation. Hereby, clear deviations between data analytics techniques can be identified. Whereas monetary impacts are particularly associated with AI and machine learning, competitive advantages are more clearly supported by articles on big data analytics or data analytics in general, which is consistent with literature that identified direct (Alshawawreh et al., 2024) or indirect effects (Rayburn et al., 2024) of big data analytics on competitive advantage. On the other hand, the small number of articles that report positive impacts on innovation do so in the context of big data analytics or specific analytics methods, but not in the context of AI and machine learning. The repeatedly appearing differences in effects of big data analytics and AI in the service sector support the current academic debate on specific affordances and limitations of AI in generating competitive advantages and innovation. Unlike other information systems, AI systems at present are characterized by important limitations in respect of strategic impacts, such as generic and not idiosyncratic nature, reliance on explicit knowledge, and a lack of contextual awareness of processes beyond AI's assigned tasks (Kemp, 2024).

6 CONCLUSION

This study investigates empirical evidence revealed in scholarly literature on the effects of data analytics in the service sector. The systematic literature review shows that data analytics provides multiple benefits to service businesses whereby impacts of different techniques are varying. Especially big data analytics and AI-based techniques show different impacts on customer response as well as effectiveness of decision-making or operational efficiency. Indirect impacts on strategic goals such as competitiveness or innovation were found less frequently, pointing at the limited scope of effects and difficulties in finding causal paths between the use of data analytics and strategic performance.

Like any research, this study shows various limitations. First, the use of data analytics techniques has been found to be heterogenous so that a finer distinction of the effects of specific techniques would yield more accurate insights. Second, the focus on English language publications and the exclusion of lower-ranked publications as well as grey literature may result in a publication bias and underrepresent insights that were published outside the investigated sample. Third, whereas the categorization of effects was achieved by open coding, a different coding approach (e.g., based on pre-determined categories from literature) could have resulted in a different pattern of impacts.

The findings of this literature review allow for refining a research agenda on a better understanding of data analytics and its impact in the service sector. First, a systematic investigation of different industries within this sector is necessary to better understand specific implications of data analytics in different service contexts. For example, AI tools can provide different value-added affordances in the healthcare sector (e.g., in the form of diagnosis) than in industries with high customer contact (e.g., in the form of service robots in the hospitality business). Since some service industries (e.g., real estate, telecommunications) are under-represented in the current body of research, more evidence is needed on such sectors in particular. Second, more research is needed to better understand the relationships between identified variables and groups of effects. This could contribute to clearer insights into the effects of data analytics on organizations' performance such as profitability or competitiveness. Third, the findings stress the high importance of an interaction between humans and information systems that are acting upon data analytics. This affects not only customer experiences and behavior, but also decision-makers and other agents in service organizations that are expected to be increasingly involved in data analytics in the future.

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