LIMITLESS PERSONALIZATION: THE ROLE OF BIG DATA IN UNVEILING SERVICE OPPORTUNITIES

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The relevance of services is increasing in the world economy, and digital technologies are boosting this process. At the same time, customers are becoming used to receiving services that are closer to their needs and expectations, and Big Data seems to play a key role in the evolution of services. This research aims to link these two trends by studying how Big Data is re-shaping service classification, thereby impacting the variables that have been used over the years to describe and classify services. This paper studies this emerging kind of services through twelve illustrative case studies based on theoretical sampling, under two variables: the extent of customer contact and the degree of customer participation and involvement. The research offers a classification of these services, discussing them under the lenses of previous models in the service field.

Keywords*: Digital Services; Big Data; Personalization; Literature Review; Mobile apps*

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1. INTRODUCTION

The history of the term "Big Data" (BD) dates back to the 90s and refers to the vast availability of data (Diebold, 2012). Over the last decade, different definitions of the term have emerged (e.g., IBM, 2012; Brown et al., 2011), highlighting the difficulties to declare what is the most appropriate "BD" (Gandomi and Haider, 2015). One of the most accepted definitions of BD (Russom, 2011; Forrester, 2012; Kwon et al., 2014) is based on three Vs: volume (the magnitude of data), variety (the structural heterogeneity in a dataset), and velocity (the rate at which data are generated and at which it should be analyzed), which have been later expanded with value (exploiting these data), veracity (using reliable data), and variability and complexity (variation in the data flow rates – in other words, inconsistent velocity – and the integration of multiple sources) (Wamba-Fosso et al., 2015).

The role of BD has been considered under different spotlights in the management field. As of now, data analytics has entered the core business and operational functions (Davenport et al., 2012). Companies have begun to see the chance to increase the effectiveness of decision-making processes within organizations (McAfee and Brynjolfsson, 2012), the chance to implement BD strategies along the entire supply chain and logistics management (Moretto et al., 2017) or the chance to implement BD analytics to increase customer satisfaction (Chau and Xu, 2012). Leeflang et al. (2014) analyzed them as a way to gain insights about customers during the customer journey. Other studies showed that BD exploitation may create a stronger and deeper relationship with the customer base (Xie et al., 2016). Eventually, BD may bring an enhanced user experience and challenge companies to think out of the box to capture new opportunities (Rust and Huang, 2014). A growing attitude towards personalization strategies corroborates these studies: users are increasingly willing to receive a service tailored to their needs, creating several opportunities from a managerial perspective (Bain Insights, 2013). This is particularly relevant in the service field, which is changing in terms of the delivery channel and experiences (Ostrom et al., 2015).

The relevance of services is increasing in the world economy, with a 10% growth in the global GDP over the last 20 years (World Bank, 2016) and, consequently, in academic literature (Biemans et al., 2016). Notwithstanding that, recent works show how changes in the external context – such as the diffusion of digital technologies and growing trends such as BD (Ostrom et al., 2015) – have not been considered in service classification and characteristics, which are often not updated (van der Valk and Axelsson, 2015). Therefore, this research aims to understand how BD is re-shaping the service classification frameworks. It is based on an extensive review of classification models and frameworks in the service field, with the aim to highlight the main variables that have been studied and used over the years. Furthermore, the relevance of these dimensions is tested in the smartphone application industry, which has been considered as one of enablers of innovation in the service experience (Dube and Helkkula, 2015).

To complement and expand the review of the literature, this paper builds on a secondary source analysis of twelve digital services. The gathered data allowed an expansion of previously described service categories to emerge, which is enabled by the opportunities provided by BD.

The contribution of this paper is related to the updation of previous service classifications, considering the impact of BD in the service offering. The framework defines four service

categories that are discussed under the lenses of previous literature.

2. THEORETICAL BACKGROUND

Two main streams of literature represent the theoretical background, focusing on services and classification model and on the impact of BD in the service field.

2.1 SERVICE CLASSIFICATION MODELS

Services –9 defined as "*processes consisting of a series of activities where many different types of resources are used in direct interaction with a customer so that a solution is found to a customer's problem*" (Grönroos, 2000, p. 48) – have a broad and variegated dedicated literature. to summarize the existing frameworks of services, we went through a systematic literature review process (Tranfield et al., 2003). The list of articles was obtained by searching publications whose titles contain at least one of the three selected keywords ("service" AND "classification", "framework", "conceptual model") on the Scopus database. We focused on papers and reviews of the Business, Management and Accounting domain, written in English. The search generated 596 results. These publications were validated for appropriateness, following which their abstract was scrutinized to retain those which were general classifications of services, avoiding the content-specific (e.g., service facilities in Tinnilä, 2012) and the product-service titles (e.g., Gaiardelli et al., 2014). Finally, 42 references were screened and carefully read. 19 papers represent the final sample (Appendix 1).

Back in the 80's, service classifications, which considers the extent of customer contact along with the degree of customization (Lovelock, 1983) was proposed. The two dimensions have been merged to study their relationship with the degree of labor intensity (Schmenner, 1986). Therefore, the three dimensions (degrees of customization, labor intensity and contact and interaction) are considered jointly, proposing a more complex service classification (Haywood-Farner, 1988).

Later, new dimensions began to get considered, such as customer participation (Silpakit and Fisk, 1985), the level of intangibility (Bowen and Jones, 1986), the degree of labor intensity (Schmenner, 1986; Haywood-Farmer, 1988), the relevance of people (Bowen, 1990) or the flexibility of the process (Wemmerlov, 1990), which were further investigated in the years that followed (Fitzsimmons et al., 1998, Karmarkar, 2004).

Silvestro and colleagues (1992) proposed a model that brings together many variables and merges them (i.e. people equipment, degree of customization, degree of discretion) to study how they vary on the basis of the customers processed by a typical unit per day. They identify three different categories: Professional Services, Service Shop, and Mass Services. They suggest an inverse relationship between the number of customers served and the level of personalization. The two opposite clusters are Professional Services, which are extremely personalized to the requests of a few customers, and Mass Services, that are standard offers to many customers. Considering the model, it appears that as the number of customers who are served increases, the service gradually gets closer to a mass service, without personalization.

Many researchers have further investigated this negative correlation effect. In their Service Process/Service Package matrix, Kellogg and Nie (1995) show an inverse relationship between the Service Process Structure (from expert services to service factories) and the Service Package Structure (from unique to generic).

In the recent years, fewer general frameworks were presented, focusing mainly on specific services (Pai et al., 2018), product-service system (Annarelli et al., 2016); or specific industries (Horng et al., 2018).

A recent literature review highlights the different variables introduced in the field. Van Der Valk and Axelsson (2015) propose an analysis of service segmentation attributes, proposing three dimensions: the extent of customer contact, degree of personalization and the degree of interaction/participation. These dimensions open up avenues for further research, given that they have often been considered in models that were somehow looking at them jointly (e.g., Silvestro and colleagues consider those dimensions on the same axis).
Recent literature considers these dimensions as relevant and worthy of further investigation, even if they emerge from dated models. Moreover, other literature show that new technologies are opening new opportunities for companies working with services (Ostrom et al., 2015; Bolton and Saxena-Iyer, 2009). This brings a continuous blend of product and service offerings (Kastalli et al., 2013) and gives a chance to service providers to exploit opportunities that were typical of products (Salonen, 2011). The following sub-section will dig in the impact that BD are having in the service field, to frame this paper in a better manner in the current debate of the service literature.

2.2 THE IMPACT OF BD IN THE SERVICE FIELD

Scholars paid significant attention to the role of technologies in re-shaping service classification and frameworks (e.g. Lerch and Gotsch, 2015) and, in particular, the digital technologies (e.g., Neu and Brown 2005). New service offering is often enabled by them (Lerch and Gotsch, 2015), re-shaping the entire supply chain (Vendrell-Herrero et al., 2016) and industry competition (Porter and Heppelmann, 2015).
All these technologies generate a huge amount and variety of data (e.g., Herterich et al., 2015), which seem to have a huge impact in the service field (Wunderlich et al., 2015). This is opening up new opportunities for value creation, enabling smart services (Allmendinger and Lombreglia, 2005) which are "*wholly different animal from the service offering of the past*" and moves from reactive to pre-emptive services, being based on the data created and analyzed by machines. In other words, smart services are delivered through intelligent objects with different sensors being able to gather data and connectivity to share them (Hoffman and Novak, 2015; Mani and Chouck, 2017).
These contributions are based on the B2B field, focusing mainly on maintenance services. Opresnik and Taisch (2015) pointed out how manufacturers can exploit significant opportunities arising from BD through servitization, eventually finding new revenue streams. Products and machines can monitor and report their conditions, enabling remote operations and the matching with external data sources, such as service histories or commodity prices (Porter and Heppelmann, 2015).
One of the first classifications of these services focuses on the different degrees of the user's and service provider's activity level, focusing on the production environments (Bolton and Saxena-Iyer, 2009). Even if the vast majority of existing literature on smart services focus on B2B environments, they are considered a growing service type, both in B2C and B2B (Wunderlich et al., 2012), even if their implications in the service literature still need exploration (Wunderlich et al., 2015).
Evidence of the usage of BD also in B2C sectors emerged (e.g., Trabucchi et al., 2017, 2018; Trabucchi and Buganza, 2019) presenting and studying the opportunities of autonomous services which may be accessible anytime and anywhere through digital devices (Ostrom et al., 2015). Nevertheless, there are still very few studies focusing on their defining characteristics (Mani and Chouck, 2018).

3. RESEARCH OBJECTIVES

On the one hand, researchers in the service field studied many variables and relationships among them, attempting to classify and create services taxonomies. On the other hand, scholars agree on the critical role of BD in unveiling new opportunities. Therefore, this research aims to understand how BD re-shaped the service classification frameworks. To clarify the overall goal of this paper, a framework summarizing the relevant dimension is needed and hereby presented.

The review of the literature highlights several dimensions that can be considered as dealing with services. To understand how the BD phenomenon is re-shaping the main dimensions of services fields, we need to focus on the most relevant ones: Degree of customization, Degree of customer contact and Degree of customer participation. These variables have often been considered simultaneously, looking at the three of them (i.e., Silvestro and colleagues, in 1992, studied these variables in the same construct in its model) or at least by merging two of them (i.e., Maister and Lovelock in 1982 and Lovelock in 1983 which merges the customer contact and the degree of participation).

New technological opportunities unveiled the chance to understand the customers and to study their preferences and needs. Digital technologies generate an amount and variety of data that allows the customization of the services (Herterich et al., 2015). This means that personalization is possible even without active customer participation, thanks to background sensors that study the consumers (Buganza et al., 2015).

In other words, a high degree of customization is enabled by the usage of BD, but it is also become a must-have feature for digital services (Leeflang et al. 2014; Trabucchi et al., 2017). Still, it is necessary to understand how BD is re-shaping the service fields impacting on the two remaining variables of services classifications: the extent of customer contact (defined as the amount of time in which the user is present while the service is being delivered, building on the chance to have the service remotely delivered as suggested by Porter and Heppelmann, 2015) and the degree of interaction and participation (defined as the extent to which the users are actively involved in the service delivery, informed by the fact that the users can be studied and observed with the service working in background, as suggested by Buganza and colleagues, 2015). Finally, following this, reasoning the specific research questions is narrowed to:

How is BD re-shaping service classifications in terms of the degree of customers contact and the degree of customer participation?

4. METHOD

The research question requires an empirical field with two main characteristics: a significant role in the service development and huge amount and variety of data during service delivery.
The Smartphone Application industry represents a proper empirical field. It played a significant role in the evolution of the service field over the last decade. Indeed, the first studies presenting "new kinds" of services directly refers to smartphones (e.g., Porter and Heppelmann, 2015). Apps are considered relevant in the service field, despite the fact that they haven't been studied adequately (Dube and Helkkula, 2015). The field is growing, with over 2 million apps available (MobileAction, 2018), with 197 billion downloads in

2017 and 258 billion estimated for 2022 (Statista, 2017a) with revenues of 188.99 billion US Dollars are expected to increase from mobile apps in 2020 from 69.7 billion in 2015 (Statista 2017b). Furthermore, this setting has often been used to develop research on BD, due to the intrinsic characteristics of smartphones and the opportunities provided by the dozens of sensors embedded in them (Trabucchi et al., 2017, 2018; Trabucchi and Buganza, 2019).

We leveraged multiple secondary-source explorations, being coherent both with previous studies in the service field with similar classification aims (e.g., Tauscher and Laudien, 2018), and recent studies regarding the usage of BD (e.g., Trabucchi et al., 2017), aiming to study the existence of different alternatives.
Using the single service as the unit of analysis of our research, a theoretical sampling approach has been selected.
To consider the huge heterogeneity of services typologies, the cases have been selected according to the four service types highlighted by Lovelock and Gummesson (2004); they are defined through the main parties involved (the presence of physical objects, the chance to process only information and the impact of customers' bodies or mind). This sampling strategy aims at increasing the external validity of the results according to two dimensions: the app category and the kind of service. We selected an app category for each kind of service. We used CrunchBase, one of the most relevant databases for digital companies, to search for companies for the sample. We searched for the category of the service needed and the words "personal*" and "custom*" in the service description, aiming to find services that could fit the aim of our research. For each query, starting from the CB ranking (the measure that represents the relevance of the company in the CrunchBase database), we selected services through the following criteria, a mobile app, as service delivery channel, the role of BD in the service delivery (assessed through the Three Vs) and the chance to offer a personalized service.
The final sample is composed of twelve cases, three for each service category, and it is summarized in Table 1, along with the defining characteristics that make the cases eligible for this research.

We used these cases as inspiration for new ideas (Siggelkow, 2007) since they "*can also help sharpen existing theory by pointing to gaps and beginning to fill them*" (Siggelkow, 2007, p. 21), coherently with the aim of this paper to expand existing theories on service operations, complementing them with the mass personalization perspective.

Type of Service (Lovelock and Gummesson, 2004)	**Examples** (Lovelock and Gummesson, 2004)	**Categories**	**Selected Cases**
Nonphysical Acts to Customers' Minds	Entertainment, news, education, consulting	Education News Music	Duolingo Flipboard Spotify
Physical Acts to Owned Objects	Freight transport, repair/ maintenance, warehousing, laundry, and cleaning	Smart home Internet of things Automotive	Nest Smartthings Automatic
Physical Acts to Customers' Bodies	Passenger transport, health care, lodging, beauty salons	Health Care Fitness Transpiration	Runkeeper MyFitnessPal Uber
Processing of Information	Internet banking, insurance, accounting, research	Navigation Fintech Insurance	Waze Credit Karma Root Insurance

Table 1 – Sampling rationale

Data gathering relied on secondary sources, searching the same information for all the cases using multiple sources. We gathered official information from the service provider, official information by App Stores and Institutional databases, articles from industry-specific and business magazines. We gathered information through the analysis of official websites and through their privacy policy, which offers in-depth insights on the kind of data that the companies gather and use, along with instructions on how to use them. The Apple App Store (e.g., the service description), the Google Play Store (e.g., download ranges), CrunchBase (e.g., monthly usage, the round of investments) and AppAnnie (e.g., release date, versions) provided descriptive data. Then, we searched for press releases regarding interviews to the founders and other articles, describing how their services worked and how they are perceived and/or delivered. We analyzed 123 articles from various sources (e.g., *Business Insider*, *CNBC*, *Financial Times*, *Forbes*, *Fortune*, *Huffington Post*). Through an iterative process, involving all the authors to reduce the personal bias, we began from the service description from institutional sources, we downloaded the apps and we analyzed the various articles searching for information or details on the how the service works to properly classify it according to the dimension of the analysis.
The analysis provided a matrix of data that allowed the authors to compare the results among the different case studies, as suggested by Miles and Huberman (1984).

5. RESULTS

To understand the degree of interaction and the extent of customer contact, results first describe the relationships between customers and services. Then, we studied the typology of data retrieved and their sources to investigate the role of BD in these services.

5.1 THE ROLE OF CUSTOMERS IN THE SERVICE

The extent of customer interaction has been defined as the amount of time in which the user is present, while the service is being delivered (Porter and Heppelmann, 2015). In a few cases, the customers' presence is necessary during the entire delivery. In other cases, however, the service continues even when the user is not present.
For example, Runkeeper turns smartphones into personal trainers with the aim of developing a smarter, more social and fun way to train (Zelman, 2012). It offers several services, such as performance tracking over time, history of activities, and so on. The customer is always present, even while the app leverages smartphones' sensors (accelerometer, GPS tracker, …) and provides real-time feedback. The same considerations can be made for Automatic, Waze, Spotify etc, that show a high extent of customer contact.

In other cases, the extent of customer contact is significantly different. For example, Nest Learning Thermostat is a self-learning thermostat that aims at optimizing the home temperature, and reducing the energy consumption (Nest, 2016). Traditionally, the users would spend time on programming it and would not change it for a long time. Nest changed this perspective: the thermostat can understand and learn people's schedules. It creates a personalized schedule in a few days. It can understand that when people leave the house and come back, increasing the accuracy of the schedule. Leveraging on built-in sensors and smartphone location, it adapts the personal schedule, allowing users to save

money and energy. It works on and analyses data even when the customer is not present. The service requires a low presence of the customers while setting the overall goal, and then works even without them. Smart Things (Samsung) and Credit Karma work in a similar way: the first always controls a customer's domestic affairs through the sensors positioned in their home, office, car etc.; while the second constantly looks for ways to save their money and monitor their credit.
The second main variable of our model is the degree of interaction and participation of the customer during the service, representing the extent to which the users are actively involved in the service delivery (Buganza et al., 2015).
In some cases (e.g.Duolingo, Credit Karma), when the customer is present, he/she interacts actively with the service: he/she provides information, performs specific actions or takes decisions to influence the development of the solution. Consider, for example, Duolingo, a language-learning service that provides its users with the opportunity to learn foreign languages through a free-of-charge business model. The CEO presents Duolingo as a personalized tutor that leverages artificial intelligence. The service requires the continuous participation of the user, who must answer the questions and listen to audio or video clips to learn a new language or take tests to evaluate the progress. This service cannot exist without a continuous interaction with the users.
Nevertheless, there are other cases (e.g. Automatic, Flipboard, Waze) that seem completely different. The customer does not have to interact with the app constantly, but the app retrieves continuously useful data for the service delivery. For example, in Waze, a community-driven GPS navigation app, the customer only has to set the final destination and the service observes how the user is driving (e.g., it senses a traffic jam if the speed decreases significantly on a highway) to merge these with the data from all the communities of users to select the best route.

5.2 THE ROLE DATA IN THE SERVICE DEVELOPMENT AND DELIVERY

Data play a fundamental role in the development of the personalized service in each of the analyzed cases, leverage on different sources. We can trace them into three categories: data provided by the user, data provided by sensors and apps, and data provided by third parties. The use of these three data sources appears to be essential for all types of services. Table 2 (available online) summarizes some examples of data retrieved in each service.
The algorithms leverage on these databases, combining several sources of data to deliver the personalized services. All the services retrieved personal information and the necessary information for the delivery of the service itself. Duolingo, for example, leverages the BD generated by users to improve the service itself, for example, by changing the usual order of the topics according to the starting language (TerrificData, 2016), or leveraging on the concept of self-regulated learning to advance the learning experience (AdaptiveLearning, 2017). Moreover, they can continuously smoothen their process by A/B testing and gathering data on the results (Veips, 2014). To do that, they leverage on Amazon DynamoDB to store the items in support of their learning service (AmazonWebServices, 2016).
The services in which the user has a less active role, leverage mainly on the data retrieved from the sensors and the app. Runkeeper, for example, continuously retrieves data from the sensors embedded in the smartphones (accelerometer, GPS tracker) and uses it to provide real-time feedback regarding fitness activities. They still use data from the users that answer a few questions regarding running abilities. An algorithm can create personalized goals, combining everything that the app knows about the user, tailoring recommendations and feedback on the user's needs and lifestyle (RunKeeper Help

Center). The company analyses the gathered data (running times, preferences, distances, and locations) to provide personalized recommendations (suggested routes according to elevation changes and distance).

6. DISCUSSION

Building on the evidence which emerges from the cases, several peculiarities of BD in the smartphone application industry emerge. For example, Duolingo leverages on the data gathered during the service delivery (the answers to the questions), to adjust the evolution of the service itself. It considers the overall amount of data to provide structural changes in the service (changing the basic model of teaching for a specific language, starting from a different mother language). Nest leverages on some user-generated input (the desired temperature) and creates a personalized thermal model, leveraging on the data gathered through the sensors embedded in the physical products, historical data and some external sources (weather forecasts). A general model is proposed in Figure 1.

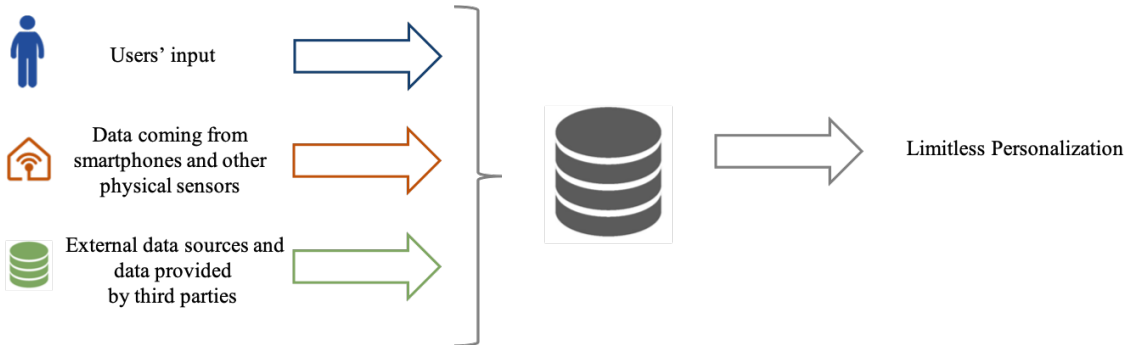

Figure 1 - Limitless personalization in data driven model

Users' set the basis for the personalization, providing information about themselves and what they want. This is the first basic principle to let them be perceived as an individual, in a personalization direction (Piller, 2007). Second, the sensors embedded in the smartphones and possibly in other smart products, works in the background (Buganza et al., 2015), observing, studying and gathering data on the users and the environment behaviors and conditions. Finally, external data sources may be integrated (e.g., wheatear condition), leveraging on existing data, instead of creating them *ex novo*.

Building on these considerations and mixing them with the two variables (to the extent of customer contacts and the degree of interaction and participation) under investigation, four categories of service emerge (Figure 2). This model answers to the research question highlighting four different kinds of services enabled by BD (Figure 2).

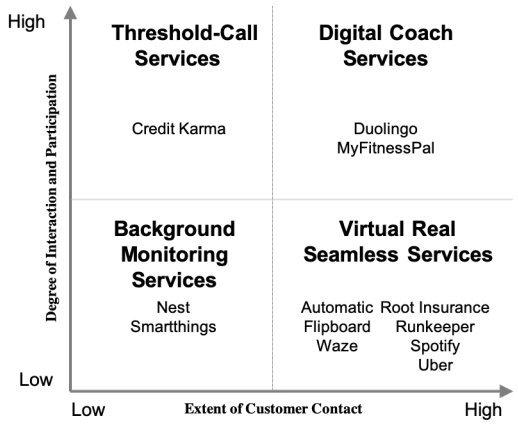

Figure 2 -A framework for Personalized Services

There are cases in which, to receive a personalized service, the customer is required to be present during the entire service delivery in a very active manner. Duolingo is a perfect exemplification of this Digital Coach Service. BD can allow customers to be considered as individuals in a personalization perspective (Piller, 2007) and they can be wherever they want to rely on connectivity (Porter and Heppelmann, 2015). Nevertheless, they are still active and present as in traditional Professional Services. This observation may provide an update to previous theories that are based on the traditional dichotomy between the personalization level and the number of customers served (e.g. Silvestro et al., 1992), but still require an important role of the customer.

The vast majority of the cases appear to be in the lower right quadrant (high customer contact, low presence): they rely on different kinds of inputs (e.g., workout target) and then consider streams of data coming from the real world around, to deliver something that fits the single user in that precise moment in time, considering customers as individuals (Piller, 2007). The vast majority of the information regarding the single customer is gathered without his/her active involvement. This is generating Virtual Real Seamless Services: they blend virtual and real worlds, providing real-world feedback (such as changes in the insurance policy owing to good behaviors or newly-released songs that should meet the listeners tastes) by observing and studying the customer in a continuous digital ethnography (Trabucchi et al., 2017).

At the same time, there is also one company that works on the opposite equilibrium (low customer contact, high presence): they are Threshold-call Services. The customer is involved where specific levels are reached or (as in the case of Credit Karma) opportunities defined through specific characteristics coming true. This type of services, even if the presence of which is smaller in our sample, are interesting from a theoretical perspective. BD has been extensively studied in the service literature to enable Smart Services, which has often been studied in B2B settings (Opresnik and Taisch, 2015), where the key characteristics are the chance to require a human interaction when decisions are required to be made (Allmendinger and Lombreglia, 2005). It seems that this quadrant may represent the B2C version of such kind of smart services.

Finally, the usage of BD enables personalized services that require lesser customer presence and a low level of participation; they are Background Monitoring Services. These services enable users to find physical objects or places in specific conditions once they have been set. The home automation field is part of this category. The role of sensors

that work in the background (Buganza et al., 2015) and the chance to rely on the Internet of Things dynamics (Mani and Chouk, 2018) play a key role. These services seem to be delivered through mobile apps to have an interaction with the final customer who sets the requirements, but they tend to have an impact on physical objects since they do not require the customer to participate physically or mentally during the delivery (Gummesson and Lovelock, 2004).
These four categories which build on literature expand previous service classification while considering how the degree of customer participation and customer contact may assume various degrees providing different kinds of services. BD emerges has the enabler of these different kinds of services, which make this research different from previous research on BD in the service filed, which focused mainly on service implementation (Gao et al., 2009; Korzun et al., 2012), or enablers (Skillen et al., 2014) rather than highlighting different kinds of services regarding the user involvement.

7. CONCLUSIONS

This paper aims at understanding how BD re-shaped and expanded service classifications in terms of degree of customers contact and degree of customer participation.
From a theoretical perspective, this research builds on traditional models (e.g., Silvestro et al., 1992; Lovelock, 1983) to show how personalization in services may take place even in the presence of a significantly high number of users and how the customer contact and the degree of customer interaction show be explored independently (Van der Valk et al., 2015) due to the opportunities unveiled by BD (Buganza et al., 2015).
It contributes to the literature proposing a service classification based on the customer involvement degrees (in a B2C perspective) enables by the usage of BD, differently from recent literature which focused on the role of BD in the service field, but without considering their classification directly and focusing on the B2B area (Allmendinger and Lombreglia, 2005; Porter and Heppelmann, 2015).
From a managerial perspective, it offers insights for practitioners aiming to develop personalized digital service. In particular, it shows how the involvement of different data sources (users' input, sensors sources) and the data retrieval in the background, with no active provision by the user may have an impact on reducing the contact time and increasing the personalization level.

This research represents a possible classification of mass-personalized services, based on a theoretical sample that is still small and biased, considering only mobile apps. The results may be expanded, considering different empirical fields or through quantitative research studies. Moreover, the users' perspective may be added, to consider their perception on the BD usage.

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