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Value co-creation between firms and customers: The role of big data-based cooperative assets

Kang Xie[a], Yao Wu[a], Jinghua Xiao[a,*], Qing Hu[b]

[a] School of Business, Sun Yat-Sen University, Xingang Xi Road, 510275, Guangzhou, China
[b] Zicklin School of Business at Baruch College of the City University of New York, USA

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ABSTRACT

To better understand how big data interconnects firms and customers in promoting value co-creation, we propose a theoretical framework of big data-based cooperative assets based on evidence of multiple case studies. We identify four types of big data resources and four types of associated digital platforms, and we explore how firms develop the cooperative assets by transforming big data resources via the theoretical lens of service-dominant logic. This study offers a new theoretical perspective on value co-creation and an alternative competitive strategy in the era of big data for firms.

1. Introduction

Value creation in the digital age has become value co-creation between firms and customers [1], and the emergence of big data has been the primary driver for this disruptive change [2,3]. On the one hand, big data has revolutionized all aspects of customer lives, which allows firms to uncover unforeseen patterns about customers, businesses, and markets [4]. On the other hand, big data offers the firms opportunities to track customer behavior and measure outcomes of competitive strategies, which demand significant organizational changes [5,6].

Of the current data volume worldwide, 90% had been generated in the last 2 years [7]. In addition, customers generate a large amount of data nowadays [6]. In the era of big data, every change in customer behavior, location, or even physiological data can be recorded and analyzed [8]. Big data has provided both significant challenges and unprecedented opportunities for firms [9]. On the one hand, the 3-V (volume, velocity, variety) features present significant challenges for data analysis [10–12]. On the other hand, the 2-V features (veracity and value) provide the potential value for firms to make better business decisions [10]. However, in practice, accurate and effective applications of big data generated by customers remain a major problem [13]. Current big data research divides data into structured and unstructured types [10,14,15]. However, business decision-making is often the result of trade-offs between costs and benefits. The traditional data classification based on structure is unable to provide the needed value reference, and it is difficult to provide practitioners guidance about how a specific type of big data resources relates to a particular type of business value. Thus, a new classification of big data based on business value is required for better business decision making.

Service-dominant (S-D) logic suggests that value is co-created by firms and customers [1,16]. Many studies focus on the conditions required for successful value co-creation [17,18] and the benefits from the co-creation [19,20]. Recent literature has started to acknowledge intangible (indirect) as well as tangible (direct) values. However, there is still a lack of clarity about different dimensions of value for both firms and customers in value co-creation. In the value literature, asset is an important concept used to describe value. Customer equity, a core concept in research from the asset perspective, is defined as the sum of the discounted expected cash flow of a firm's current and potential customers [21,22]. However, this concept of asset frequently adopts a goods-dominant (G-D) logic and views customers as passive assets. Extant customer equity studies emphasize the direct economic value created from customer purchasing behavior and the direct economic expectation derived from the total number of customers [23].

We argue that it is necessary to advance an asset-based concept to highlight the characteristics of value derived from the cooperation between firms and customers. In the current literature, although value co-creation is a cooperative phenomenon, research tends to focus on the benefits each actor receives

* Corresponding author.
E-mail addresses: mnsxk@mail.sysu.edu.cn (K. Xie), sandywu2550@126.com (Y. Wu), lnsxjh@mail.sysu.edu.cn (J. Xiao), Qing.Hu@baruch.cuny.edu (Q. Hu).

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without considering the shared benefits between firms and customers at the same time. There is no theoretical concept in the literature that describes the shared benefits created by the cooperative behavior. We combine the concept of asset with S-D logic to propose a new concept—cooperative assets—defined as a type of asset with probable current or future economic benefits that can be acquired or controlled by the cooperative actors through service exchange. This study suggests that if firms and customers want to accomplish value co-creation, they must become cooperative assets to the other party. This study describes the specific transformation process of cooperative assets and identifies three characteristics of the cooperative assets that differ from the traditional assets: interactive, integrative, and bilateral. The bilateral characteristic is rooted in the nature of "cooperation" and "co-creation," which makes cooperative assets a unique category in the value co-creation scenarios.

Cooperative assets may be created from various ways, e.g., relation-based cooperative assets. In this study, we focus on the cooperative assets created from big data, and we argue that cooperative assets relate to big data in the following aspects. First, the resource basis of cooperative assets consists of two parts: customer-generated big data resources and firm-provided big data platforms. Using an exploratory case study approach, we identify four types of big data resources and four corresponding big data platforms. Second, based on the new data and platform classification, we propose four types of cooperative assets. This work essentially links resources (big data resources) to assets (concrete value) and enhances understanding of the value of big data in value co-creation. The current market competition is increasingly becoming data competition, and businesses are relying on technology to compete [24]. A clear understanding of how big data transforms from resources to valuable cooperative assets will have a profound impact on contemporary competition.

Goes [24] suggests that open and interdisciplinary academic research is helpful in understanding the value of big data. By connecting big data to S-D logic, this study proposes a theoretical framework of cooperative assets, which extends extant research in at least three ways. First, we identify four types of big data resources from different customer roles and identify the benefits firms can acquire from those resources. This provides a new big data classification that could guide practitioners to link particular data resources with a corresponding economic value. Second, both "value" and "co-creation" are metaphorical in construction [25]. This study provides a more specific description of value co-created by the actors and reduces the abstraction and ambiguity in understanding value. This study explains the bilateral benefits obtained by firms and customers through cooperation, demonstrates the process of co-creation, and interprets the consequences of co-creation. Third, although the potential benefits of big data are real and significant [2], and big data has been recognized as a new form of capital [26], few academic studies provide a consolidated framework to explain how big data becomes assets that generate value to the actors in value co-creation. This study interconnects big data and S-D logic, and illustrates the process of big data transformation from resources to assets.

The rest of this paper is structured as follows. We first describe the theoretical foundation of this study and present a gap analysis in Section 2. We then present our research methods and a detailed explication of data collection and analysis in Section 3. In Section 4, we describe a comprehensive process of big data transformation from resources to assets. We explicate four types of cooperative assets that provide bilateral benefits. In Section 5, we discuss the characteristics of cooperative assets and propose a theoretical framework, as well as the study's theoretical and practical implications, limitations, and ideas for future research. Finally, we summarize the main findings of this study in Section 6.

2. Theoretical background

2.1. Service-dominant logic and value co-creation

S-D logic is one of the most important theories that explain value co-creation between firms and customers [16,27]. S-D logic defines "service" as the application of specialized competences for the benefit of another actor or the self [27,28]. Distinct from G-D logic, S-D logic emphasizes that service is the fundamental component of economic exchange [27]. Goods are only distribution mechanisms for service provision, not a unique expression of value [16]. Firms are described as contributors, not simply product providers, to help customers accomplish one or more jobs (i.e., achieve a goal, resolve a problem, or satisfy demand) [1,29,30].

Another contribution of S-D logic is that it challenges traditional value creation logic, which implies that value is transferred from firms to customers. S-D logic clarifies that value is customer centric and co-created by both firms and customers [1,28]. Value co-creation research defines co-creation as joint actions by a customer and a service provider through direct interactions [25]. Recent value co-creation studies by marketing scholars focus on exploring the processes of value co-creation between firms and customers [28,31,32] in which *role changes*, *resource integration*, and *value identification* remain key focal discussion points.

2.1.1. Role changes

S-D logic repositions the role of firms and customers within the value co-creation context, which is a shared worldview among value co-creation researchers. Firms are viewed as service providers [16,27], and resource integration is considered fundamental for service provision in S-D logic [1,33,34]. Specifically, firms integrate two types of resources to accomplish service provision: tangible resources, such as physical resources, human resources, partners, and customer resources [25,32], and intangible resources, such as knowledge and skills of the actors in value-creating networks [16,27]. Building digital platforms is an important way for the integration of resources by firms [35]. Therefore, we use "platform provider" to summarize the role of firms as the service provider in value co-creation with customers in big data environment.

In the S-D logic literature, customers are viewed as "operant resources," that is, they are capable of integrating skills and knowledge into co-creation processes [16,27]. Lusch and Nambisan [34] identify three broad roles of customers depending on the nature of service exchange and the type of resource integration achieved: ideator, designer, and intermediary. According to Lusch and Nambisan [34] (2015, pp.168), "The role of *ideator* reflects customer capability to bring knowledge concerning their needs and unique work to the firm context and to integrate it with knowledge concerning their use of existing market offerings to envision new services. The role of *designer* reflects customer capability to mix and match existing knowledge components or resources to configure or develop new services. The *intermediary* role reflects customer capability to cross-pollinate knowledge across multiple ecosystems and serve as intermediaries in service innovation. In this role, customers help make non-obvious connections across ecosystems in ways that provide value for themselves and others."

Previous studies have explained how firms participate in value co-creation and how their value is created [1,36]. By contrast, the same questions from the customer perspective are not adequately addressed. A conjecture is that prior studies assume customers are "service beneficiaries," which eliminates the relevance of explaining the customers' role in value co-creation. Lusch and Nambisan [34] argue that the value an actor creates or co-creates may not be directly related to the use of the offering; rather, it may pertain to the broader context in which such a role is enacted. Some studies suggest that different roles of customers may produce different value [37]. Therefore, the three different roles of customers in the value co-creation context proposed by Lusch and Nambisan [34] help explain how customers create value and the different types of value they create. However, this view has not been discussed further in the extant literature.

2.1.2. Resource integration

S-D logic views all actors as resource integrators, including firms and customers [34]. Arthur [38] argues that actors integrate resources for two primary reasons. First, any resource obtained by an actor cannot be used in isolation. It must be combined or bundled with other resources to be useful or valuable. For instance, customer demand is a type of information resource. Information resources must be combined with corresponding information technology (IT) applications for latent commercial value. Second, innovation is often the result of recombining existing resources. For instance, IT is combined with other resources (e.g., actors' skills and knowledge) to allow information to be transmitted and repackaged in different contexts for new service exchange and innovation opportunities [39].

Firms and customers integrate resources in different ways. Firms integrate market resources, individual resources, and public resources using operating platforms [1]. Customers, on the other hand, integrate social network resources and individual resources (e.g., their knowledge) to participate in value co-creation [34]. Although resource integration is equally important for customers to accomplish co-creation, few studies have considered how different customer roles integrate resources and how they affect the results of value co-creation. This study argues that customers with different roles may exhibit distinct participative behavior on digital platforms, which produce different types of big data resources. These distinct customer-generated big data resources have an impact on the process and results of value co-creation.

2.1.3. Value identification

S-D logic suggests that value is co-created and shared by firms and customers [1,16]. In other words, both firms and customers are beneficiaries of cooperation [40]. There are two theoretical perspectives to examine the benefits customers create for firms: the value perspective and the asset perspective. The *value perspective* has explored both direct value and indirect value for firms [17,19,20]. This stream of research focuses on theoretical explanations but not in the pursuit of quantitative measurement of value. For example, Kumar et al. [17] suggest a new term, "customer engagement value," to describe the value to a firm of co-creation processes. According to Kumar et al. [17], customer engagement value is divided into four components: customer lifetime value (reflecting customer buying behavior), customer referral value (new customers attracted), customer influencer value (ability to influence existing and potential customers by spreading word-of-mouth communication), and customer knowledge value (received from customer feedback, such as ideas for innovation and improvements).

Compared to the value perspective, the *asset perspective* focuses on economic value by providing quantitative measurements when describing "value." However, the emphasis of this stream of research is on customer purchasing behavior [41,42], not on a comprehensive interpretation of customer behavior (e.g., non-transactional behavior). Customer equity, a core concept in the asset perspective, is defined as the sum of discounted expected cash flow of a firm's current and future customers [21,22]. Previous studies that consider customers as assets emphasize the direct economic value created from customer purchasing behavior and the direct economic expectation derived from the total number of customers [23]. This is because of two main reasons. First, the G-D logic suggests that only firms play the role of value provision. Second, the benefits from non-transactional behavior are difficult to measure and estimate, which limits in-depth quantitative research of customer assets.

In addition, the concept of customer assets or customer equity implies the way in which firms use customers, a typical G-D logic. It is difficult to use this concept or its underlying value logic to explain the value co-created by firms and customers. In a mutually beneficial context, an actor's benefits depend on how "adaptive" the actor is, that is, the actor's ability to cooperate with the others [16]. In this study, we argue that the change in marketing logic (from G-D to S-D) requires rethinking of asset-related concepts. Traditional asset-related concepts must be reconceptualized to highlight the characteristics of value in the co-creating context. Moreover, although value co-creating practices are already widespread, academic studies still tend to focus on the value of a single actor, and there is no theoretical concept that captures the shared benefits created by cooperative behavior of the participating actors.

We attempt to combine the concept of assets with S-D logic to propose a new concept—cooperative assets. We submit that cooperative assets differ from customer assets or customer equity in at least three important aspects. First, cooperative assets emphasize that the value of non-transactional behavior is as important as that of transactional behavior. Second, assets are created through the interaction between firms and customers, that is, value is co-created by both actors, not supplied by one to the other. Finally, the value of cooperative assets is bilateral, i.e., value is shared between both firms and customers.

2.2. The relevance of big data and value co-creation

2.2.1. The impacts of information technology on service-dominant logic

IT has greatly facilitated interaction between customers and firms in value co-creation [43]. Internet-based technologies have empowered customers and compelled firms to be more customer-centric [44–46], which has driven firms to be more service dominated. The advent of the Internet significantly reduced information asymmetry between firms and customers, increased customers' bargaining power and, consequently, changed the channel power structure [47]. Moreover, the Internet strengthens interactions among customers, unifies unconsolidated individuals into powerful communities, and facilitates customer influence on firms [48]. Negative comments and public sentiments generated by online customers diffuse even faster and have significant impacts on sales, product/service design, production, and consumption [49]. As a result, the Internet intensifies market competition and increases the difficulty for firms to maintain strategic competitive advantages [50]. Thus, to excavate customer data and analyze potential demand in advance of competitors have become a fundamental requirement for firms in the fiercely competitive global market [51,52].

IT also enables convenient collection of customer data, superior communication with customers, and effective response to changes in low-cost and highly efficient ways [53–55]. Therefore, IT is a technological enabler for firms to exercise a service-dominated strategy. The increasing use of IT and big data-related technologies enables firms to sense, capture, and respond to market changes [53,56,57], and helps firms manage big data generated by customers [58]. In essence, IT has provided the necessary technological infrastructure and low-cost social transaction foundation that enable firms to adopt a customer-centric orientation and the S-D logic in designing their business strategies.

2.2.2. Big data and value co-creation

Big data is generated primarily by customers and can be used to portray customer behavior and reflect their value co-creating actions. Big data generated by customers has the typical characteristics of 3-Vs (volume, velocity, and variety) [59]. For example, online shopping produces transactional data, and Internet surfing and search generate trajectory browsing data. When customers exchange opinions or ideas in a virtual community, these interactions generate data [58,60]. When customers participate in value co-creation process, for example, designing a customized product on a digital platform, their actions are recorded as data and collected by firms for analysis [8]. Therefore, big data generated by customers captures the significant relationship between the consumers and the firms.

On the other hand, prior studies show that analyzing customer big data benefits firms with regard to precision marketing, new product development, and realigning business strategy to maintain sustainable competitive advantage [61–63]. However, the 3-Vs of big data create great challenges in data analysis [10–12]. Although big data is viewed as a new form of capital [26], many firms are unable to excavate its value effectively [64]. Studies often divide big data into two types: structured data, which typically includes ratings, questions with binary answers, or questions with a limited range of responses, and unstructured data, which is amorphous and must be preprocessed to be usable [10,14]. This classification of big data is primarily based on data analysis considerations [10], and we argue that it does not reflect different types of data values that result from different customer behaviors or actions. Without a value-based classification of big data, it is difficult to link a specific type of big data resource to a particular type of value in the value co-creation process. Therefore, we argue that classifying consumer big data from a value perspective is a critical step in understanding value co-creation.

Meanwhile, big data platforms represent an important channel for firms to co-create value with customers. Big data platforms, in this study, refer to the digital service platforms enabled by big data technologies. These platforms enhance the efficiency and effectiveness of service exchange by making resources liquid, increasing resource density, and facilitating easy access to appropriate resource bundles [34]. Big data platforms range from common online transactional platforms (transactional exchanges), virtual social networking platforms (consumer community communication), open-design platforms (customer self-help design), and mobile interaction platforms (firm–customer communication). In recent years, widespread use of digital platforms has enabled groups of individual customers to congregate virtually and pursue desired products/services or shared interests, despite being separated by time and space [65]. Although studies have examined the role of digital platforms in value co-creation [66], the focus has been on the firms and their partners, while the role of consumers has not been explored.

In summary, although big data has been viewed as a new form of capital, few, if any, academic studies have explored how big data is transformed from a digital resource to a valuable asset. While technical discussions on big data analytics and algorithms are abundant [11,67], a comprehensive theoretical framework of big data as cooperative assets and its role in value co-creation is absent in the literature. As market competition increasingly becomes data competition, a better understanding of how big data transforms from resources to valuable and governable assets is required for creating and sustaining competitive advantages.

3. Research methodology

3.1. Case study design and case selection

To accomplish our research objectives, we selected a theory-driven exploratory case study approach for the following reasons. First, this study explores how big data interconnects firms and customers to facilitate value co-creation. An exploratory case study is preferred when addressing such "how" questions because of its holistic and descriptive nature [68]. Second, value co-creation between firms and customers occurs in complex and dynamic processes. Both "value" and "co-creation" are strongly metaphorical in their construction [25]. An exploratory case study could help explore such complex and contextual phenomena, explicate key ideas from complicated processes, and determine the potential of those ideas in the given context [69]. In addition, a case study approach better fits the dynamic interactive processes between firms and customers in value co-creation by providing descriptive evidence [70]. Third, few studies have explored the role of big data in value co-creation between firms and customers. Therefore, this research field is still in its nascent form. A theory-driven exploratory case study is preferred in order to identify new theoretical constructs, build a new theoretical framework, and advance previous research in this context [71].

A central decision in case study design is the number of cases to include in a research project [72]. Compared to a single case, multiple cases follow replication logic, which means that each case must be selected carefully so that it presents either similar results (a literal replication) or contrasting results for anticipatable reasons (a theoretical replication) [68]. We designed this study with literal replication logic to establish a general theoretical framework of cooperative assets. We chose two case firms from the clothing industry for the first step. Thereafter, we chose another two case firms from the furniture industry, as we planned to explore the similarities of big data-based cooperative assets among the four selected case firms in different industries with different sizes selling different products. This design makes it relatively easy to compare our findings, to increase their reliability, and to decrease their sensitivity [70]. We selected our sample using three criteria. First, the selected case firms have consciously co-created with customers instead of acting as supply monopolists in markets. Second, the selected case firms are representative, i.e., they are frontrunners in their market segments. Third, the case study firms belong to different industries, are of different sizes, and sell different products. The two selected industries represent two of the most popular e-commerce marketplaces in China.[1] Table 1 shows the profiles of the four selected case firms.

3.2. Case firm description

Firm A was founded in 2006. It was a business-to-customer company and became the leading firm in the Chinese market with its own clothing brand. Annual sales reached 10 million RMB (about 1.5 million USD) in 2007 and rose to one billion RMB (about 150 million USD) in 2012 with 300% annual growth. The company has more than 10 million loyal customers. Firm A paid close attention to customer communication and responded quickly to customized demand. The firm provided various digital platforms to support communication with consumers and introduced advanced

[1] The Chinese E-Commerce Research Center (CECRC) reported in 2015 that Chinese online clothing transaction sales in 2014 reached 434 billion RMB (about 66 billion USD), and became the leading category for online product sales; and the sale of Chinese online furniture reached 119 billion RMB (about 18 billion USD) in 2014, and is predicted to reach 205 billion RMB (about 31 billion USD) in 2015.

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Table 1
Case firm profiles (as of 2014).

Firm	Industry	Ownership	No. of staff	Annual sales (RMB)
A	Clothing	Privately held	~2000	~1 billion
B	Clothing	Privately held	~1300	~1.5 billion
C	Furniture	Privately held	~300	~0.3 billion
D	Furniture	Publicly traded	~6000	~6 billion

IT applications to acquire customer feedback, which steered the entire supply chain synergistically toward satisfying customized demand. In addition, with the help of data analytics, Firm A is continuously revising its marketing strategy, products/services, and even organizational structure to maintain sustainable competitive advantages.

Firm B was established in 2008. It is known for its original clothing design and was named the "cotton and linen artist." The firm has maintained fast sales growth alongside unique, original design. In 2014, its annual sales reached two billion RMB (about 300 million USD). Firm B devoted itself to establishing a firm–customer co-creating platform. The firm launched its official mobile application and built multiple virtual communities, which allowed designers, managers, and customers to communicate directly on clothing design philosophy or consumption experience. Regular customers expressed their opinions on upcoming products or provided advice to others on fashion coordination and styling outfits. In addition, Firm B invited customers to become shop-keepers of online-to-offline stores in order to attract and service new customers.

Firm C was founded in 2008. It was a pioneer in the online cartoon furniture segment in China. In 2011, Firm C attempted to extend its sales channels to the Internet and reached sales of 10 million RMB (about 1.5 million USD) and 28 million RMB (about 4.2 million USD) during the "Single's Day"[2]; one-day sales event in 2012 and 2013, respectively. The company successively acquired exclusive licenses from top global and domestic cartoon brands[3] to use their cartoon images on its products for the Chinese children's furniture market. Firm C gradually developed into the leader of a new manufacturing industry that creatively integrates toys, animation, home furniture, and the Internet. From 2014, Firm C began to invite its customers to participate in product improvements and marketing promotions with digital applications and mobile platforms. In 2015, Firm C advanced to a new level by launching the "Cool Mom and Dad Marketing Plan," in which customers were organized to participate in marketing value co-creation.

Firm D was established in 2003. The firm was listed on the Shenzhen Stock Exchange in 2011, the first customized wardrobe company to list on the stock market. Annual sales reached six billion RMB (about 900 million USD) in 2014, and online sales accounted for 5% of total sales. Firm D focuses on providing customer-to-business customized furniture. Using big data analytics, the firm matches customized demand to mass production. Firm D collects customer data through the direct-linked CRM system of franchisers and digital platforms. These data are then transmitted to and processed by an internal enterprise resource planning (ERP) system. The firm centralizes control and integrates information systems in different franchisers and departments, and effectively converts data resources to customized furniture. Moreover, Firm D has launched advanced IT applications and built digital platforms to enable customer participation in value co-creation.

3.3. Data collection

We designed data collection with interviews of selected informants in the case firms in two phases: the initial data collection and then follow-up in-depth data collections. The entire data collection lasted from the year 2008 to the year 2015. In the initial data collection, we introduced our research objectives to the target informants of the case firm. We discussed general research and background questions with the informants to assess the suitability of the firms for the research topic. In the in-depth data collection, the research team conducted focused interviews with each selected informants addressing the research questions and background information about industry, market, and firm specifics. At least three members of the research team were involved in each interview. One or two researchers acted as the chief interviewer, and others interjected with questions whenever appropriate. All interviews were recorded digitally and transcribed and reviewed as quickly as possible after each interview was completed. The research team held frequent discussions to articulate and debate core concepts and emerging theoretical frameworks. Different interviews with informants were arranged with time lags, which allowed the research team time to organize, digest, and absorb evidence and examine the emergent frameworks.

We selected top executives, top management team members, as well as frontline employees as informants for this study in order to gather reliable case evidence and facilitate cross validation via triangulation. In the in-depth data collection phase, the research team visited Firm A five times and conducted 21 interviews with 12 individuals, resulting in approximately 1710 min of digital recording and averaging over 81 min for each interview. The research team visited Firm B three times and organized 18 interviews with 15 individuals, resulting in approximately 908 min of digital recording and averaging over 50 min for each interview. Based on the case evidence collected from Firm A and B, we identified core concepts and developed a preliminary theoretical framework. Then, the research team investigated Firm C and D to acquire further evidence for cross validation. The research team visited Firm C seven times and conducted 27 interviews with 14 individuals, resulting in approximately 2265 min of digital recording and averaging over 84 min for each interview. The research team visited Firm D twice and conducted 12 interviews with six individuals, resulting in approximately 716 min of digital recording and averaging over 60 min for each interviewee. The details of the informant profiles are shown in Table 2.

We used semi-structured interviews as the main data collection approach, supplemented by field observation and secondary Internet data searches. We used a variety of data sources and data triangulation to improve data validity [72], including: 1) secondary materials, such as Internet data on the company website, books, literature, newspapers, and other reports; 2) archive files, mainly acquired from companies internally, such as PowerPoint presentations, product manuals and catalogs, and promotional videos; 3) field observations, such as company department visits, product gallery, or product line; 4) informal conversation, such as communicating with shopping guides in a service experience store or online customer service staff; and 5) firsthand experience, such as shopping in online-to-offline stores. These approaches enriched our case data and increased the reliability of the study.

[2] "Single's Day" (Double-eleven Festival) is a holiday every November 11. It has become the biggest e-commerce festival in China and has repeatedly broken online sales records set in previous years.

[3] These brands include Disney, Hello Kitty, SpongeBob SquarePants, Pleasant Goat and Big Wolf, and Ali.

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Table 2
Profiles of Informants.

Firm	Recording Time	No. of interviews	No. of interviewees	Job Titles
A	1710 min	21	12	Chief Executive Officer(CEO)(4), Executive Assistant(4), Vice President(2), Administrative Assistant(1), Deputy Director of IT(3), Deputy Director of Commodity Department(1), Assistant to Director of IT(1), Director of Operations (1), Director of Recruitment(1), After-sales Manager(2), Salesperson A of Flagship Store(1), Salesperson B of Flagship Store(1)
B	908 min	18	15	Chairman of the Board(1), Assistant to Chairman(2), Director of Brand Design(1), Director of Operating Center(1), Director of Management Center(1), Chief Financial Officer(1), Vice President of Public Affairs(1), Operation Executive (2), Administrative Assistant(1), Vice President of Human Resources(1), Vice President of Mobile Communication(2), Project Director of O2O(1), IT Manager(1), Customer Service Supervisor(1), Planning Manager(1)
C	2265 min	27	14	Chief Executive Officer(CEO)(3[4]), Vice President for Supply Chain(1), Vice President for Marketing(3), Vice President for Retailing(1), Brand Director(1), Deputy Director of Finance(3), Product Director of R&D(2), Furnishing Design Director(1), Director of Distribution(2), Director of Human Resources(1), Deputy Director of Sales(1), Manager of T-mall franchise house(1), Director of Marketing(1), Deputy Director of Marketing(1)
D	716 min	12	6	Chairman of the Board(1), CEO(2), Assistant to Chairman(2), General Manager of Information Management Center(3), Data Manager of Information Management Center(2), Vice President of Marketing Center(2)
Total	5599 min	78	47	

3.4. Data analysis

In the data analysis phase, we followed the exploratory case study methodology proposed by Yin [68] and used an open coding approach. First, three researchers coded the transcripts of each case independently. Referring to the preliminary theoretical framework, the researchers identified core concepts, their logical relationships, and key supporting statements. In this stage, the coding results of the three researchers were compared, and, if disagreements occurred, discussions followed to improve consistency. In the second stage, following the replication logic [68], the three researchers compared the four cases and extracted the similarities in the different cases. In this stage, various tables were constructed for comparative analysis. If different opinions occurred, we revisited the literature and transcripts to revise the findings. Finally, we arrived at convincing explanations of the coded results. For replication and theoretical saturation [68], we alternated between the extant literature and the coded results. If theoretical saturation failed to emerge, the steps were repeated. If evidence was missing or conflicting points occurred in the dataset, we called back the relevant interviewees. Unrelated or isolated events and concepts were dropped from the final evidence set of this study but were maintained in the case database for future analysis.

4. Research findings

In this section, we describe a comprehensive process of transforming big data from resources to cooperative assets by explaining its resource basis, capability basis, and type of cooperative assets based on the case evidence we collected and analyzed via the process described above.

4.1. Resource basis of cooperative assets

Our case study evidence suggests that the resource basis of cooperative assets consists of two components: the first derives from customer-generated big data information resources and the second from firm-provided big data platform resources. In the following analysis, we describe the two types of resource basis in detail.

[4] The number of interviews organized for one individual.

4.1.1. Customer-generated big data information resources

From the case evidence, we find that different customer roles generate different types of big data information resources, which constitute a resource base for customers to participate in value co-creation. Drawing on Lusch and Nanbisan [34], we identify four types of big data generated from the four different customer roles: buyer, ideator, designer and intermediary.[5]

Transactional big data:

The buyer role of customers generates transactional big data. Purchasing behavior is the main source of transactional big data. All four case study firms mentioned that one of the most frequently used types of big data is sourced partly from online orders generated by customers. As customers shop online, their trading behavior is recorded and generates transactional big data, including price, product category, color, numbers, buying cycle, location, and demographics.

Communication big data:

The role of ideator generates communication big data. Communication with firms when purchasing through interactive websites, instant message, and telephone lines produces unstructured communication data. For instance, the after-sales manager of Firm A informed us that customer feedback or complaints to the call center were translated into digital records for analysis; some customers preferred to consult online customer service staff or put forward personalized demands through instant message software, such as Aliwangwang,[6] or QQ[7] before they made a purchase decision. These dialogues were recorded and stored in databases. In addition, customer product reviews or new product trial reports are also components of the communication data.

Group communication behavior generates communication big data that is non-transactional. Customers use virtual social platforms that are either provided or built by firms. For example, Firm B built a mobile fan club taking the theme of "fashion coordination," "wardrobe maintenance," and "fashion and make-up." In this virtual community, customers share their clothing style or outfit experiences with words or pictures. Some customers might ask others for help or freely discuss interesting topics. As Firm B's product categories expanded, topics and themes in the

[5] Lusch and Nambisan [34] proposed three roles (ideator, designer, and intermediary) that reflect non-transactional behavior; we added the role of buyer to capture transactional behavior that is a major characteristic of customers.
[6] Produce of Alibaba.
[7] Product of Tencent.

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virtual club increased, ranging from clothing to lifestyle. Various interest groups formed in the virtual club, such as a makeup group, a cooking group, a clothing group, and even a culture group. As mentioned by the customer service supervisor of Firm B, "*The information generated from customer group communications hides mountains of value. Their favorite topics, puzzles, emotional feelings, or characteristics could be reflected by these data.*"

Participative big data:

The designer role of customers generates participative big data. Participative big data refers to the data generated by customers who actively participate in product or service development using their knowledge, resources, and skills.

Distinct from transactional or communication big data, participative big data is oriented toward the re/configuration of specific products or new services. The planning manager of Firm B stated that each year, the firm would choose a city from which to get inspirations for new product design (e.g., the Town of Phoenix, an ancient city with a romantic legend in southern China). To select a location, Firm B organized its regular customers to vote for a city that they preferred and allowed customers to be decision makers. Customers participated in this activity with the help of online interactive technologies and an official mobile forum operated by the firm. Customers were quite familiar with the firm's brand image and could express their ideas and share their travel experiences in alternative cities to help determine the location. An example how customers helped firms improve their designs is described by the vice president of Firm B:

> *"It was in 2014. Yunnan was chosen as the location from which new clothing inspirations would be extracted and expressed on our new arrivals [seasonal designs]. However, when these new arrivals came to market, our fans' feedback through our mobile forum and official online platform reflected the opinions that the design of the new clothing resembled the brand image of LIEBO (an ethnic-style clothing brand from a competitor of Firm B). Our fans voiced that excessive ethnic elements in the clothing design weakened our unique brand image. We immediately improved the product and received high praises [from those fans]."*

For Firm D, some customers actively participated in customized furniture design and provided individual ideas and demand information. In addition, Firm C provided user-friendly software for design by customers. Customers could drag the virtual models of the furniture into diagrams that mimicked their homes. All these participative features accurately reflect personalized demand and generate substantial amounts of participative big data.

Transboundary big data:

The intermediary customer role generates transboundary big data. Transboundary big data refers to data generated by customers who share different service ecosystems and facilitate the export and import of knowledge across different ecosystem boundaries.

Customers act as intermediaries because the Internet significantly reduces switching cost and searching cost for customers and enables them to try different brands, products, or purchases on different online platforms. This transboundary customer behavior facilitates knowledge sharing in different ecosystems. For example, the CEO of Firm C informed us that Taobao, which is ranked as the leading online shopping platform in China by Alexa and iResearch, influenced the online purchasing habits of a majority of customers. Customers who shop online typically expect that products should be delivered within 7 days, but this is challenging for a furniture company, such as Firm C. Producing and delivering furniture by traditional methods may require up to 60 days. Subsequently, in the earlier stage, Firm C suffered negative evaluations and complaints because delivery services were in stark contrast to the services provided by other e-commerce providers. The vice president of marketing of Firm C provided another vivid example:

> *"Cash-on-delivery service is quite normal for e-commerce when you buy general commodities, like books, clothing, food, and even expensive electronic products. But it is very rare in the furniture industry. However, we gradually found that more and more customers asked us 'Why can't I order this furniture with cash-on-delivery service?' Similar inquiries or reviews frequently appeared. This drove us to recognize that our customers need this service. So, what we needed to do was to try to advance the payment method of furniture orders to fit e-commerce habits."*

4.1.2. Firm-provided big data platform resources

According to the case evidence, we find that big data platforms constitute a resource base for firms involved in value co-creation with customers. Different digital platforms with heterogeneous features support the generation, collection, analysis, and feedback of corresponding types of big data resources. We identify four types of firm-provided big data platforms: transactional platforms, communication platforms, participative platforms, and trans-boundary platforms.

Transactional platform:

A transactional platform is a digital service platform that supports customer purchasing and enables the collection of transactional big data, the transmission of data for analysis, and rapid responses back to customers. All four case firms established their own online transactional platforms and simultaneously participated in large online shopping platforms owned by third parties. The majority of sales for Firm A originated from its official online platform, and Firm A also cooperated with T-Mall and JD.com, two top online shopping platforms in China. The majority of sales for Firm B originated from T-Mall, and Firm B cooperated with JD.com and Amazon. Firm C and Firm D obtained their sales mainly from T-Mall and participated in multiple online channels, such as JD.com, Amazon, and VIP.com. Through their own transactional platforms, these firms conveniently acquire transactional big data and transmit data for analysis using directly linked information systems, such as ERP and CRM. In addition, with three-party transactional platforms, these firms obtain basic transactional data and can buy more comprehensive data. The vice president for retailing in Firm C commented:

> *"Big data we acquire from these transactional platforms helps us systematically comprehend customer purchasing behavior, such as their purchase frequency, consumption, and products they look for or continue to focus on. We could obtain and utilize these data. For example, if a customer has browsed bed linen twice in a month, we will push a marketing advertisement or product list to this customer."*

Typically, an *ad hoc* data department is designated for the collection of transactional big data and share to other departments. For example, the CRM department in Firm B is responsible for transactional big data collection. After collecting daily or weekly data, the CRM department sends the data to other departments for data analysis. The planning department analyzes the popularity of new products from the datasets; the CRM department analyzes the buying cycle of multi-brand products; the customer service department analyzes customer satisfaction, and the advertising department analyzes the shopping paths from which customers have been sourced.[8] In addition, different transactional platforms enable different ways of information sharing. For instance, the

[8] As interpreted by the interviewees, firms or the third party could monitor customer-shopping paths by embedding the tracking software. This software could identify the source of customers, for instance, the Google browser, BAIDU browser, or other mobile applications. This data analysis contributes to advertising and media planning decisions.

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shopping guides of Firm C uses an iPad to retrieve data for regular customers' past orders, preferences, and other member information. This shared information assists the shopping guides in the provision of customized services.

Communication platform:

Communication platforms are digital service platforms that support customer group communication and enable the collection and transmission of communication big data. Generally, communication platforms are built by firms who want to attract customers with different themes. In our case firms, Firm A and Firm B founded their own clothing-fit forums. Specifically, Firm A developed a fan club on BAIDU to support the discussion of fashion and makeup coordination. Firm B set up a fan club primarily based on mobile applications to support the theme of "slow life in cities," which involved a wide range of lifestyle subjects. Popular subjects were advocated by customers and spread across different communication channels. Backstage technologies enabled customers to stay, review, give thumbs-up, or forward their favorite threads. Opinion leaders may emerge after frequent interactions. Some firms grant opinion leaders certain authority, such as casting a ballot for controversial topics. The CEO of Firm A commented:

"From the start, we rewarded club members with bonus points to encourage them to make a blueprint on the forum. Some active members who had creative practices could become 'blueprint talent.' Later, many members actively participated in commenting or forwarding hot pictures or topics that made 'comment talent.' These customers share their shopping experience or their creative life inside the club."

Similarly, Firm C established a mobile interactive platform called "Let's Chat, Mums!" for its regular customers, based on Webchat. Mothers could write and publish their ideas or post pictures. The content was shared among all members on this platform. Other customers could provide praise for mothers' contributions by clicking the "like" button. The more "likes" a customer received, the more bonus points would be awarded.

Participative platform:

Participative platforms are digital service platforms that support firms' effect to attract customers to participate actively in product improvement and to re/configure new services or new business decisions. For example, Firm B developed a mobile application for direct communication among firm managers, designers, and regular customers. Before Firm B launched a new product, a representative would exhibit the product on the application and request feedback from customers. For personalized products, Firm B would motivate customers to participate and share their ideas concerning new fashion elements. The data collected on this participative platform is shared among other managers, designers, and customers.

Another example is the children's room open-design platform developed by Firm C. This is an easy-to-use furniture design software. Consumers can simply drag the virtual furniture onto their virtual apartment diagrams. The CEO of Firm C commented:

"This open design platform is capable of supporting personalized design requirements, such as self-help children's room design. It is also a database and call center with a home-design portfolio, product library, and solution gallery. Customers can engage in online self-design or make an appointment for in-home service. Designers can provide online support or provide home services."

Transboundary platform:

Transboundary learning platforms are digital service platforms that support firms in acquiring new knowledge shared by customers who build connections across diverse ecosystems. Establishing or joining a multi-brand and multi-industrial virtual community is an efficient approach for firms establishing a transboundary platform. For example, clothing retail companies, such as Firm A and Firm B, joined in third-party online clothing customer communities, like Meilishuo, Duitang, and Mogujie. Both Firm A and Firm B set up an *ad hoc* data team or department to collect and analyze transboundary big data to capture shared heterogeneous knowledge, such as advanced service designs of other companies, popular fashion elements of clothing, or new customer communication channels. By analyzing this transboundary big data, firms can quickly sense and adapt to new changes. In addition, Firm A and Firm B established their own virtual clothing design communities. These communities attract new customers who are interested in the brands of Firm A and Firm B. New potential customers consult and share product opinions, which in turn help firms acquire transboundary information. Similarly, for furniture retail companies, such as Firm C and Firm D, third-party furniture-related web portals are valuable. For example, in May 2014, Firm C gained access to the three largest web portals of the mother-and-infant market in China: YaoLan.com, YaYa.com, and Mom.com. By August 2014, the number of Firm C supporters had grown to more than 50,000. By introducing new customers, Firm C captured more heterogeneous information and expanded its product categories to include new household products and air filtering machines.

4.2. Capability basis: from heterogeneous resources to cooperative assets

The customer-generated big data resources and the firm provided big data platforms are heterogeneous and not inherently integrated resources that can be readily used in value co-creation process. According to our case evidence, we propose that if firms and customers want to engage in value co-creation processes, they need to capitalize the heterogeneous digital resources through cooperative capability. In this study, we define "cooperation" as one actor's behavior in creating value for the other actor. Specifically, from the perspective of value as assets, cooperative capability reflects the ability of an actor to transform the heterogeneous resources into valuable and governable assets. Based on the study case evidence, we describe how firms and customers may apply big data-related abilities to capitalize heterogeneous digital resources for value co-creation.

First, customers can be capitalized as cooperative assets of firms because customer-generated big data resources can be obtained or controlled easily by firms through digital platforms, and these heterogeneous digital resources are beneficial for firms. This capitalization from resources to assets depends on three big data-related abilities applied by firms: the ability to acquire, analyze, and commercialize big data.

Big data acquisition refers to data collection, storage, and transmission. Our case studies show that firms can leverage transactional and communication platforms to collect, transmit, and store transactional and communication big data. Customers constantly generate copious amounts of big data. If firms are unable to collect this big data in a low-cost and highly efficient manner, they do not possess the fundamental prerequisites to capitalize the big data information resources.

For the purpose of obtaining or controlling customer big data information resources, firms' ability to analyze and use big data determines whether these digital resources create economic benefits for firms. Our case evidence shows that firms apply big data analytics to identify the business opportunities hidden in volume and multi-dimensional big data. For example, Firm B launched a new brand of yoga clothes because it discovered demand from transactional big data, which indicated that the total demand for women's sportswear was expanding. As another example, Firm A applied the big data of trial sales and return visits to perfect their clothing design gradually.

Firms' ability to transform digital resources to improve products or new business strategies represents a type of dynamic capability that enables firms to adapt quickly to fluctuating environments. Firm C, for example, through the analysis of sales records and marketing feedback from the fans, found that some regular customers were effective marketers, because their recommendations were more readily accepted by their relatives, friends, or peers. Therefore, the top management team of Firm C rapidly replaced the traditional hierarchical organizational structure with independent departments with directionally supported marketing by fans in different regions. In addition, Firm C improved mobile interconnection techniques by resolving delays in transmitting reward feedback, which further strengthened the synergy between customers and firm representatives. A series of measures improved the effectiveness of marketing promotion and attracted new customers.

On the other hand, firms can be capitalized as cooperative assets of customers because firm-provided big data platforms can be accessed or used easily by customers, and these heterogeneous digital resources are beneficial for customers. This capitalization from resources to assets depends on three big data-related abilities possessed by customers: the ability to search for information, to learn new technologies, and to participate in value co-creation.

Customer ability to search for information and the ability to learn new technologies determine whether firm-provided platforms are accessed or used by the customers. By searching for information, customers experience various digital platforms provided by firms and acquire needed information. As mentioned by the deputy director of IT in Firm A, "*if customers are deficient in searching for effective information, or they still are used to applying outdated channels for search, these customers might be unable to connect with our advanced digital platforms.*" Therefore, information searching is fundamental for consumer participation in value co-creation.

The cases of Firm B and Firm D indicate that regular customers with higher brand loyalty showed a greater interest in new technologies launched by the firms and adapted more quickly to advanced digital platforms. For example, when Firm B launched its children's room open-design software, some fans learned to use this application quickly. If they were confused by the simulation layout, they would seek online support from professional designers. As customers learned and adapted to this new technology, they were able to design spaces by themselves. In contrast, if they were unable to learn, their participative behavior would be handicapped.

Through information searching and learning, a portion of customers develops the ability to participate in value co-creation. Our case evidence shows that the greater the participating ability, the more benefits the customers will be able to acquire. For instance, in customer group communications, opinion leaders obtain more social attention and privileges compared to the average participants. Again, some customers do not simply buy from clothing trading platforms, they design and match clothes according to their creative style and taste and recommend them to others in the online communities. As they reach a level of popularity, they are invited by the clothing companies to be involved in product improvements, recommendations, or new product design, and to receive the appropriate material reward. Some companies even transform these fashion experts into professional product buyers and from customers to value co-creators.

The analysis in this subsection shows that three big data-related abilities applied by firms (the ability to acquire, analyze, and use big data) form the cooperative capability of firms to capitalize heterogeneous consumer resources. Three big data-related abilities applied by customers (the ability to search for information, learn new technologies, and participate in value co-creation) form the cooperative capability of customers to capitalize heterogeneous firm resources.

4.3. Cooperative assets: bilateral benefits

Our case evidence shows that cooperative assets provide bilateral benefits to the cooperative actors in value co-creation processes. Both firms and customers benefit from the cooperation. Follow the analytical logic in Subsections 4.1 and 4.2, in this section, we identify four types of cooperative assets: transactional cooperative assets, communication cooperative assets, participative cooperative assets, and transboundary cooperative assets. The bilateral benefit of each of these different cooperative assets are discussed.

Transactional cooperative assets bring transactional benefits to the customers and the firms. Transactional benefits for the firms are reflected in the enhancement of sales performance. In our cases, all four companies were highly focused on the analysis of structured order data (e.g., price, color, quantity, and purchase cycle) and unstructured communication data (e.g., consumer reviews and pre-sales communication) to improve product sales and consumer satisfaction. For example, the vice president of Firm B mentioned that the firm extracted data from the order system to identify the consumption cycle and found that most of the core customers were accustomed to purchasing twice a month. This result prompted Firm B to change the frequency of new arrival introductions, which encouraged regular customers to buy more frequently. In addition, feedback from the returns collected by the customer service department helped revise products and services, which improved customer satisfaction and improved business transaction performance. The customer service supervisor for Firm B stated:

> *"Every time a consumer returns an item, customer service will take the initiative to communicate and, ask 'Why do you want to return the product?' or 'Why do you want to change the size?' Customers will give you the appropriate information as feedback. For example, 'This dress is too big,' or 'The clothing displayed on the website did not match my expectations,' or 'The product was damaged during distribution.' Business processes will be adjusted in accordance with this data analysis to bring our products more in line with consumer expectations."*

Customer transactional benefits are reflected in the economic gains in customer transactions or activities associated with a transaction. We identify three customer transactional benefits. First, satisfaction from business exchanges. A convenient trading platform provided by firms helps identify what customers need and allows them to enjoy fast and hassle-free return services. Second, economic benefits by building a bridge between firms and new customers. This reflects the interests of consumers who act as transactional intermediaries. Firm C gave their fans individual marketing identities (IDs). Fans could advertise, share, and recommend Firm C's products or even recount their experiences using Firm C's furniture with real-life pictures. If fans successfully promoted the product, the information systems would record their IDs, and the company would rewarded these customers with bonus points according to their sales. Bonus points accumulated could be used in exchange for Firm C products. Third, indirect economic benefits from business exchanges. Customers who become corporate members can enjoy the preferential trading offered by third-party corporate partners. As the member of Firm C (a majority of consumers are mothers), customers are given a 20%

discount when purchasing a bakery birthday cake in community convenience stores.

Communication cooperative assets have a positive impact on firms with marketing benefits, such as improvements in corporate marketing activities in terms of efficiency or effectiveness. Information sharing among consumers will enhance their understanding of the brand, thereby strengthening brand awareness and loyalty. For example, interviewees of Firm B and Firm C mentioned that in their officially established virtual community, opinion leaders or active users tended to have high customer loyalty and were familiar with the brand culture and product characteristics. These fans often promoted the brand. The director of brand design of Firm B stated:

"Customers in some communities are very active. We found that they not only share their ideas about outfits but also help other consumers to solve fashion problems. For example, some consumers would ask what make-up to wear with this style of clothing. They would communicate with each other with this type of question. Such exchanges increase customer usage of the community and benefit our brand stickiness."

Communication cooperative assets also bring customers social benefits. Social benefits reflect the emotional satisfaction or social capital that customers possess. According to our case evidence, customers make friends through virtual communication platforms. An important reason that unacquainted customers become friends is that the virtual communication platforms are built based on certain themes or interests. Therefore, customers with the same problem (e.g., how to choose children's furniture) or a common interest (e.g., a preference for cotton clothing) are attracted to each other. Customers use communication platforms to interact with other customers by asking, answering, or sharing ideas from which they build friendships. Moreover, Firm C supported face-to-face customer communication by inviting fans who are mothers to drink coffee together or participate in in-store group activities. This promoted mutual awareness, as described by the marketing director of Firm C:

"Our fans really like to take their children to the store to participate in group activities, such as childcare activity. We hold this type of activity from time to time, especially at some festivals, such as Children's Day. We arranged a series of group activities, for example, lectures of formaldehyde prevention and family games. Moms and kids recognize each other and the children play together. There is a lot of talk among the mothers."

Participative cooperative assets mainly bring operating benefits for firms. Operating benefits reflect improvements in operational efficiency or effectiveness. Using Firm B as an example, consumers vote for new locations of new product launches. In this case, consumer engagement in product/service development can help firms improve operational efficiency or effectiveness. The vice president of Firm B stated as follows:

"The choices made by customers through voting better reflect their needs and preferences. Therefore, customers are more valuable. The conventional mode of this type of decision making in companies was brainstorming, which not only requires lots of meeting but is not necessarily in line with customer expectations. Now, we choose to let customers determine where the new product is designed because their participation enhances the effectiveness of this business operation."

Another example is the children's furniture open-design platform. Customer self-service furniture design greatly advanced the efficiency and effectiveness of furniture design. If customers do not participate in the design operation, the designers must visit the customer's home and take measurements themselves. In addition, designers need to assess customer preferences to provide a selection of plans. Even with these elements, designers may still not be able to meet the customer expectations. Now, with the furniture open-design platform, customers can express individual needs through self-design, and designers can amend the designs to meet professional standards. This increases the satisfaction of consumers with the furniture design and enhances operational efficiency.

Participative cooperative assets primarily bring customized benefits for customers. Customized benefits are realized when firms re/configure product/service in accordance with the specific recommendations or requests of customers, and they are equivalent to a customized offering from the firms to these customers. Firm B seeks advice from the regular customers before new product launches. Customers can express their preferences for new clothing features and elements. Designers collect and analyze these preference data and design according to consumer input. Therefore, customers who participate in developing new products are offered customized products that carry their favorite clothing elements and features. As another example, customers who are involved in furniture design can satisfy the individual needs of their home design. Many respondents of Firm C and Firm D stated that customers who were deeply involved in furniture design obtained greater satisfaction from the customized products.

Transboundary cooperative assets bring knowledge benefits for both firms and consumers. Firms can analyze transboundary data to acquire heterogeneous knowledge shared by customers of other brands. The data manager of the information management center of Firm D stated that they acquired and analyzed mountains of data every day from the multi-brand and multi-industrial virtual communities to track changes in marketing models and update trends of new business technologies. In addition, transboundary learning helps firms identify differentiated brand appeal and capture heterogeneous marketing knowledge. This helps firms to adjust their market positioning, business strategy, or product/service development. Meanwhile, consumers can search and become familiar with similar brands or products/services through the transboundary platforms to enhance their knowledge of brands or products/services from different firms and competitors, which helps them optimize the brand selection and purchase decisions.

4.4. A process model for the formation of cooperative assets

Based on the analysis in the above sections, we propose a process model to describe the formation of cooperative assets in the value co-creation operations between customers and firms, as shown in Fig. 1.

The process model is straightforward and self-explanatory in depicting how cooperative assets are created from two types of big data resources in the value co-creation process between customers and firms. Interactions between the four types of big data resources and the four types of digital platforms transform these resources into four categories of cooperative assets through the applications of customer and firm cooperative capability. However, the characteristics of the cooperative assets need further explanation. Based on our case evidence, we identify three major characteristics of the cooperative assets: interactive, integrative, and bilateral.

Interactive characteristic: Consistent with S-D logic [1,27], cooperative assets are formed through continuous, iterative exchange between firms and customers. This characteristic differentiates cooperative assets from traditional assets. Traditional assets, such as equipment and factories, are created or owned without multi-actor interactions. Our findings show that different interactions produce different values. Specifically,

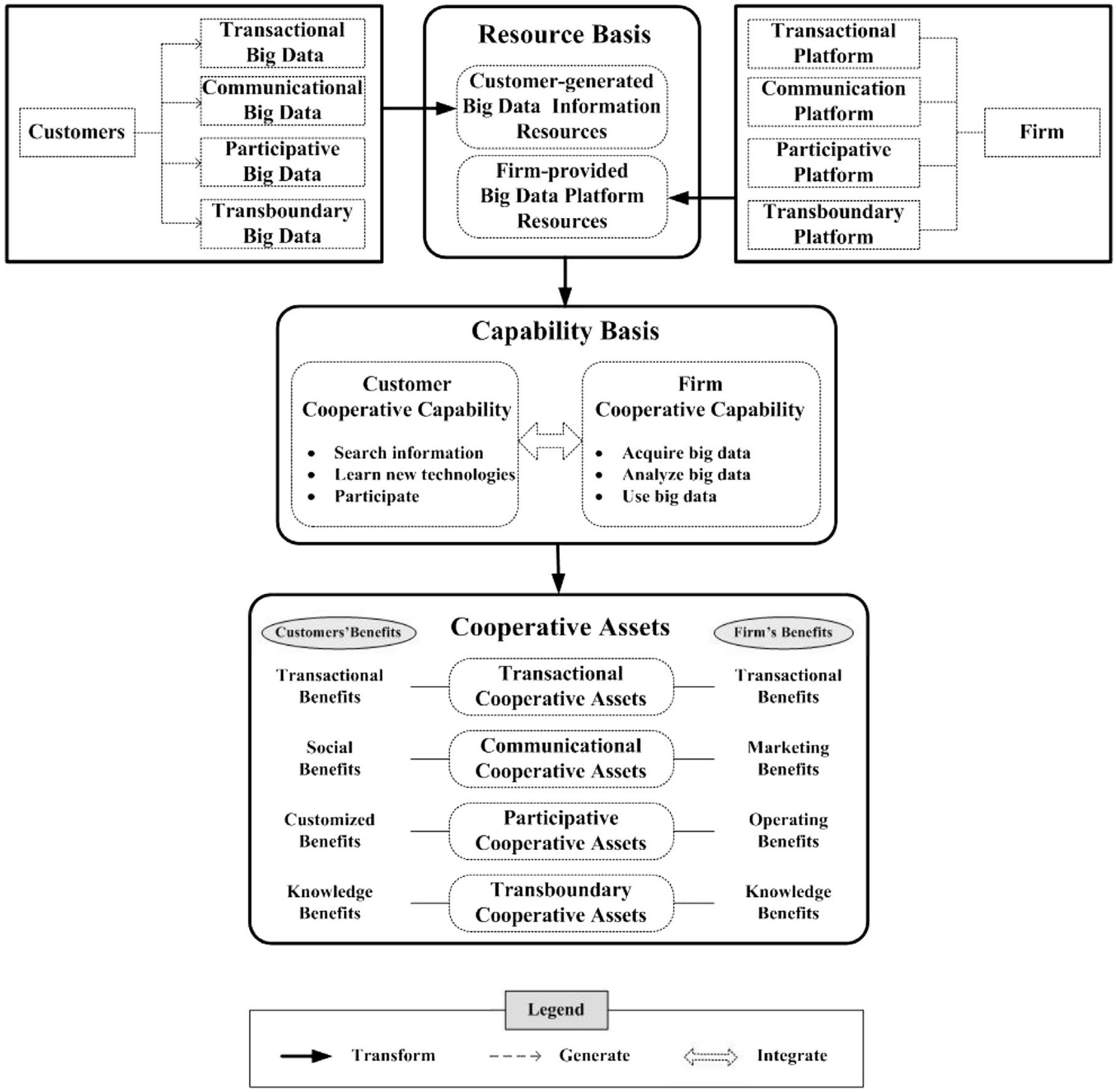

Fig. 1. The process of model of cooperative assets formation.

transactional interactions between firms and customers generates transactional big data resources, which guide transactional operations and improves sales performance. Communication interactions between customers generate communication big data resources, which are the basis for data analytics on customer needs. Participative interactions between firms and customers generate participative big data resources with which firms can improve business processes and re/configure product/service. Transboundary interactions generate transboundary big data resources, which help firms and customers to acquire heterogeneous knowledge. Thus, the foundation of cooperative assets is the interactions between the cooperative actors. Thus, if there is no interaction, an actor might own digital resources but be incapable of transforming the resources into cooperative assets.

Integrative characteristic: Integration is the second foundation for cooperative asset formation. Cooperative assets are formed through the integration of heterogeneous digital resources. Our case findings show that cooperative assets are not a simple aggregation of customer resources and firm resources. Instead, their formation relies on the integration of big data resources and the related abilities applied by the cooperative actors. We have established that the abilities of customers to search for information, learn new technologies, and participate are key to configure diverse resources and transform these resources into cooperative benefits. We have also shown that the abilities of firms to acquire, analyze, and use big data help firms acquire and integrate heterogeneous knowledge resources and transform these resources into real economic value.

Bilateral characteristic: The bilateral characteristic indicate that the benefits created by the cooperative assets are shared by the two actors in the value co-creation process. In our research findings, we discussed how four types of cooperative assets benefit firms and customers in specific ways. Bilateral benefits reflect the nature of "cooperation" and "co-creation." This characteristic highlights that cooperative assets are a unique theoretical concept in the context of value co-creation.

5. Discussions

In this section, we summarize our main findings with a theoretical framework that defines the main theoretical constructs and the relationships among them. We also present discussions about the theoretical and practical implications of these findings, limitations of this study, and directions for future research.

5.1. A theoretical framework: from service-dominant logic to cooperative assets

Based on the research findings, we propose a theoretical framework for big data-based cooperative assets. This study suggests that in the context of big data, generating data is the primary contribution of customers to value co-creation, and providing a digital platform that facilitates the collection, storage, and analysis of the data is the primary contribution of firms to value co-creation. For firms and customers alike, big data based digital resources are valuable resources to acquire and control, and become most valuable if they are transformed into cooperative assets. Fig. 2 illustrates a theoretical framework that links the key elements of big data resources with cooperative assets from the lens of S-D logic. This framework depicts the intricate relationships among big data resources and customer and firm capabilities at three levels: resource integration level, service exchange level, and cooperative asset level.

Resource integration level: This level demonstrates the resource basis for cooperative assets. According to our findings, heterogeneous digital resources represent the resource basis for cooperative assets. Two types of heterogeneous digital resources emerged in this study: customer-generated big data information resources and firm-provided big data digital platforms. Through the integration of heterogeneous digital resources, the actors apply their unique capabilities to co-create value.

Service exchange level: This level demonstrates the capability basis of cooperative assets. Our findings indicate that simply owning heterogeneous digital resources is not equivalent to possessing cooperative assets. Only when heterogeneous digital resources are use through cooperation can it be transformed into valuable assets. We suggest that firm–customer service exchange is the primary means of such cooperation. Vargo and Lusch [16,27] argue that "service" is the application of specialized competences. We extend this view and propose that cooperative capability represents the essence of the "specialized competences" in service exchanges. Therefore, service exchange emerges via cooperative behavior and the use of cooperative capability by both parties.

Cooperative assets level: Through resource integration and service exchange, firms and customers become cooperative assets with current or future economic benefits that could be acquired or controlled by the other actor in the value co-creation process. Service exchange between the firms and the customers enhances their participation and interaction, which further increases their reliance on each other and their expectations for value co-creation. This cooperative behavior facilitates further service exchange and triggers new big data generation and new resource-integrating behavior.

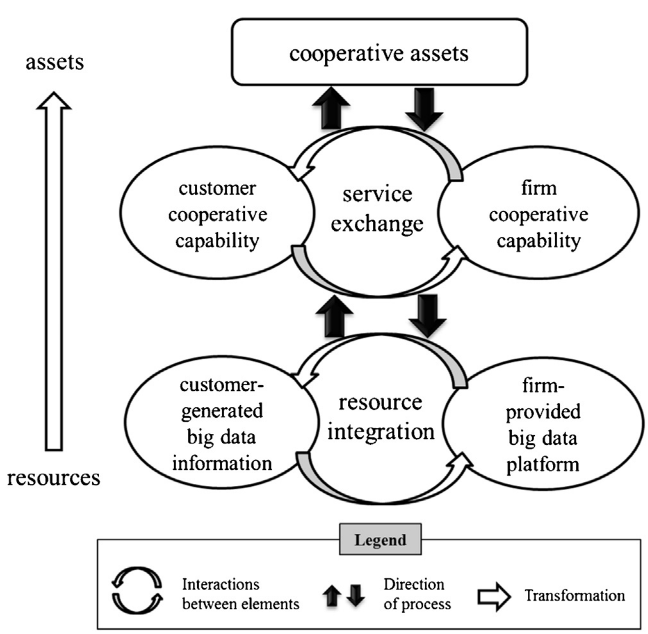

Fig. 2. A theoretical framework of cooperative assets.

5.2. Theoretical contributions

This theoretical framework follows the spirit of S-D logic and suggests that technological elements, such as digital forums, social media channels, and digital platforms for big data collection, storage, and analysis, are the fundamental components of value co-creation, instead of being simply implicit premises. We believe that this theoretical framework for cooperative assets advances extant research in at least three ways.

First, this study provides guidance for big data classification from a value co-creation perspective. Prior studies divide big data into structured and unstructured data from the perspective of technical analysis [10,14,15] and determine the value of data by optimizing algorithms [11,67]. However, corporate decision-making is often the result of the trade-off between costs and benefits. Traditional data classification based on structures is unable to provide the required value reference and makes it difficult to guide practitioners for strategic decision-making. In addition, this structure-based big data classification do not reflect the distinct data value resulting from different customer behavior. Our research findings reveal that value-based big data classification is an important step in steering data analysis techniques. Based on the research of Lusch and Nambisan [34], we identify four types of consumer roles in a value co-creation context—the buyer, ideator, designer, and intermediary—and analyze four different big data information resources generated by the four consumer roles: transactional, communicational, participative, and transboundary. This study details the differentiated value obtained from the big data resource, and provides a new way of thinking for understanding the value of big data and guiding data analysis.

Second, this study enriches value co-creation research from an asset perspective. Although the S-D logic indicates that value is co-created and shared by firms and customers [1,16], the value interpretation of the asset still follows the G-D logic, which considers customers a passive asset. There is still a lack of clarity in defining different dimensions that constitute cooperative value for both firms and customers in value co-creation. This study explains how cooperative assets form and identifies three differentiated features of the cooperative assets: 1) the potential value of non-transactional customers is equally import as the tangible economic benefits of transactional customers; 2) assets are formed through the interactions of actors in the value co-creation process; and 3) benefits from cooperative assets are bilateral and shared. This study provides a specific description of value co-created by actors and, thus, reduces abstraction and ambiguity in the literature.

Third, this study enriches the theoretical perspective on how big data resources become cooperative assets. Although big data has been recognized as a new form of capital in the literature [26], few academic studies have provided an in-depth analysis of how big data becomes value assets. This study, from the lens of S-D logic, illustrates the process of transforming big data from resources to cooperative assets. Our findings show that transforming digital resources into value assets requires a heterogeneous resource base and cooperative capabilities. Merely owning heterogeneous data resources will not necessarily result in the formation of cooperative assets. Only when the actors in the value co-creation process have the capability to cooperate are they able to transform isolated resources into value assets. This study shows that the cooperative capability of firms consists of the capability to acquire, analyze, and use big data. These capabilities allow firms to capitalize on the heterogeneous customer data effectively; and the cooperative capability of customers consists of the capability to search for information, learn new technologies, and participate in value co-creation.

5.3. Practical implications

This study also has multiple implications for practitioners to navigate the turbulent waters of transitioning from industrial age enterprises to digital era competitors. First, the study of cooperative assets explains why traditional firms should invest in digital platforms that facilitate the collection, storage, and analysis of customer generated big data. Our findings show that such investment allows the firms to transform customer-generated big data resources into valuable cooperative assets. The value of the cooperative assets is realized through customer participation in improving existing or creating new products and services.

Second, this study provides a new idea for customer valuation for firms. Previous valuation approaches are based primarily on the number of current and expected customers. This study suggests that in the digital era, firms should be more concerned with cooperative assets created through firm and customer interactions and the different values from different types of interactions. This study identifies four types of cooperative assets and analyzes the benefits for firms from each. This research finding provides a reference for firms to assess the value of different consumer roles and how to acquire these values. For example, if customers execute the intermediary role effectively through a transboundary platform, firms may gain better knowledge that helps foster better market sensitivity and promote the rapid innovation.

Third, our study offers an alternative business strategy for firms to address the fierce competition in the digital era. Competitive advantages, such as better products or lower prices, may no longer be effective in addressing issues like customer defection due to low switching costs and numerous alternatives. A stable cooperative relationship can be established only when firms engage in value co-creation with customers through service exchanges and mutual support as the actors evolve into cooperative assets. The sustainability of the cooperative relationship is greater than that of the "customer relationship." This is because when customers are viewed simply as "passive value recipients," they can effectively switch between different firms or brands. By contrast, when firms are capable of offering digital platforms for customers to participate in value co-creation, customer participation produces stronger path-dependent behavior that firmly connects them with firms.

5.4. Limitations and future research

As an exploratory case study, this study inevitably has some limitations that also provide opportunities for future research. First, compared to other customer equity studies, this study primarily focuses on qualitative descriptions, because value co-creation involves large numbers of intangible and indirect benefits that cannot be measured easily. One potential future research is to develop better measurements for the key constructs in the framework proposed in this study. Second, we identify four types of big data platforms from the four case studies. However, this does not exclude the possibility of other types of digital platforms or capabilities. We focus on these four types of platforms because: 1) they are typical in the business context, and 2) the four digital platforms correspond to the four types of customer roles, which better reflects the interaction and exchange of the two actors in value co-creation processes. Future research may expand the number of cases in order to obtain findings that are more robust. Moreover, due to limited space, we primarily focus on the comprehensive process of big data from digital resources to cooperative assets, which, in varying degrees, limited our analysis on the associations between some key constructs, such as the four types of cooperative assets. Future research may elaborate on these associations by using more selected case evidence. Finally, to simplify the discussion of value co-creation and focus on developing the concept of cooperative assets, we consider only firms and customers as the two main actors in value co-creation processes. However, a comprehensive service exchange system involves other important actors, such as partners, governments, and other stakeholders. Future research may explore how multiple actors evolve into mutual cooperative assets and develop a broader framework and understanding for the formation of cooperative assets in value co-creation processes.

6. Conclusion

Despite the fact that big data is recognized as a new form of capital in the digital era, little research has been done about how big data becomes valuable assets to customers and firms. Based on evidence from multiple cases, this study proposes a process model that describes how big data is transformed from resources into cooperative assets in value co-creation processes. We identify four types of customer roles in value co-creation context and analyze four different big data information resources generated by these roles: transactional, communicational, participative, and transboundary. We find that cooperative assets are created through the interactions of actors in the value co-creation process, and the benefits from the cooperative assets are bilateral and shared between the participating actors. Last but not the least, we find that transforming digital resources into value assets requires applying heterogeneous resource bases and cooperative capabilities from both actors. This study connects big data with S-D logic, and theorizes the process of big data transformation from resources to assets. Thus, this study provides new insights for academics and practitioners for understanding what big data value is and where it comes from. This study also calls for more future research on the value of big data within the value co-creation context in order to develop better insights on competitive strategy in the big data era.

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Kang Xie is a Professor in the Business School at Sun Yat-sen University, Guangzhou, China. He received his Ph.D. from Renmin University, China. He teaches IT management strategy, electronic commerce, and information economics at graduate and undergraduate levels. His research primarily focuses on IT strategic management, the role and value of IT in organizations, and inter-organizational IT governance. He has published 12 books and many papers in leading academic journals, including *European Journal of Information Systems*. His research has been funded by NSFC (National Science Foundation of China), NSSFC (National Social Science Foundation of China), and Chinese government ministries and state agencies. He is also an IT management consultant for many government agencies and private enterprises in China.

Yao Wu is a doctoral candidate in Information Systems in the Business School at Sun Yat-sen University, Guangzhou, China. Her research interests include ecommerce strategy, supply chain and IT integration, and information economics. She has presented her work at multiple national and international conferences, including the International Conference on Information Systems (ICIS) and the Pacific Asia Conference on Information Systems (PACIS).

Jinghua Xiao is an Associate Professor in the Business School at Sun Yat-sen University, Guangzhou, China. She teaches IT management strategy, electronic commerce, and information economics at graduate and undergraduate levels. Her research primarily focuses on the strategic role of information technology in organizations, supply chain management systems, and inter-organizational IT governance. She has published in leading Chinese and international academic journals, including *Journal of Management Information Systems* and *European Journal of Information Systems*. Her research has been funded by NSFC (National Science Foundation of China). She is also an IT management consultant for many government agencies and private enterprises in China.

Qing Hu is Professor of Information Systems and Associate Dean for Academic Initiatives and Innovation in the Zicklin School of Business at Baruch College of the City University of New York. He received his Ph.D. from the University of Miami in Florida, USA. He teaches IT strategy, information security, and systems development at graduate and undergraduate levels. His research focuses on the impact of IT on organizational strategy, culture, security, and performance. His work has been published in premier academic journals including *MIS Quarterly, Information Systems Research, Journal of Management Information Systems, California Management Review, Decision Sciences,* and *IEEE Transactions on Software Engineering,* He served as an *ad hoc* associate editor for *MIS Quarterly* and *European Journal of Information Systems* and was on the review panels for the National Science Foundation of the USA.

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