Data analytics capability and servitization: The moderated mediation role of bricolage and innovation orientation

Abstract

Purpose – Despite the potential influence of data analytics capability on servitization, our understanding of the underlying mechanisms of this influence remains unclear. This study explores how data analytics capability affects servitization by examining the mediation effect of bricolage and the conditional role of innovation orientation.

Design/methodology/approach – This study employs the moderated mediation method to examine the proposed research model with archival data and multiple-respondent surveys from 1,206 top managers of 402 manufacturing firms in the Yangtze River Delta area in China.

Findings – Bricolage partially mediates the positive relationship between data analytics capability and servitization, and innovation orientation positively moderates this effect.

Practical implications – Manufacturers can leverage bricolage to materialize data analytics capability for servitization. Manufacturers should also pursue an innovation orientation to fully glean the benefits of bricolage in transforming data analytics capability into servitization.

Originality/value – This study opens the black box of how data analytics capability affects servitization by revealing the underlying mechanism of bricolage and the boundary condition role of innovation orientation for this mechanism. It offers valuable insights for practitioners to leverage data analytics to improve servitization through developing bricolage and cultivating a culture of innovation orientation.

Keywords – Data analytics capability, Servitization, Bricolage, Innovation orientation

1. Introduction

The proliferation of big data, coupled with advances in data analytics, has provided tremendous opportunities for manufacturers to pivot toward *servitization* (Brinch, 2018; Hsuan *et al.*, 2021), which is defined as the addition of services to manufacturers' core product offerings to create new value for customers (Raddats *et al*., 2019; Sousa and da Silveira, 2019). Data analytics provides powerful tools to analyze big data associated with products, customers, and markets (Grover *et al.*, 2018), enabling manufacturers to derive valuable insights to sense and seize servitization opportunities (Opresnik and Taisch, 2015). Therefore, *data analytics capability*, the ability to use analytical tools and processes to analyze big data and derive insights for decision-making (Srinivasan and Swink, 2018), has been considered a critical enabler of servitization (Ardolino *et al.*, 2018). Rolls-Royce, for example, efficiently leverages its data analytics capability to analyze the operating data of aircraft engines and diagnose engine health, which enables the provision of services such as engine remote monitoring and maintenance (Harrison, 2017).

However, despite the strong appeal of data analytics capability, many manufacturers struggle to harness it for improving servitization (Kohtamäki *et al.*, 2020; Tronvoll *et al.*, 2020). For example, equipped with superior data analytics capability, GE launched the GE Digital initiative in 2015, endeavoring to develop software service for industrial equipment and become a "top 10 software company" by 2020 (Krauskopf, 2015). However, this initiative was undermined by technical complexity, resulting in GE spinning it off (Tronvoll *et al.*, 2020). This anecdotal case suggests that data analytics capability does not automatically enhance servitization (Coreynen *et al.*, 2017). To fully unleash its potential, manufacturers need to identify the underlying mechanisms that convert the advantages of data analytics into improved servitization (Tronvoll *et al.*, 2020). Recent information systems studies suggest that the effects of data analytics capability on business outcomes could be indirect and mediated by other firm capabilities (e.g., Ciampi *et al.*, 2021; Mikalef *et al.*, 2020). Although pioneering servitization research based on conceptual analysis or qualitative case studies has explored the influence of data analytics capability on servitization (e.g., Ardolino *et al.*, 2018; Opresnik and Taisch, 2015), few quantitative studies have identified and attested the underlying mechanisms through which data analytics capability is converted into improved servitization. Such a void constrains comprehensive and generalized understandings about the value of data analytics capabilities for servitization.

To address this gap, this study proposes that *bricolage*, the ability of "making do by applying combinations of the resources at hand to new problems and opportunities" (Baker and Nelson, 2005, p. 333), may function as a critical mediator through which data analytics capability affects servitization. It has been demonstrated that bricolage is particularly important for servitization (Witell *et al.*, 2017) due to its role in tackling resources constraints that impede servitization (Eggert *et al.*, 2014). The combined resource requirements of service provisions and tangible product business may dilute limited organizational resources (Fang *et al.*, 2008; Witell *et al.*, 2017), which leads servitizing manufacturers to struggle with resource constraints such as lack of service technicians, inadequate customer support facilities, and shortage of financial capital

(Kreye, 2017; Raja *et al.*, 2018). Bricolage empowers manufacturers to recombine and reuse resources at hand to resolve resource constraints (Witell *et al.*, 2017) and provides resource support in transferring the insights derived from data analytics to service offerings. Meanwhile, data analytics capability is conducive to recombining and reusing existing resources based on insights extracted from big data (Chen *et al.*, 2015). In this sense, data analytics capability may facilitate servitization by improving bricolage that addresses resource constraints. Accordingly, this research endeavors to close a gap in the literature by investigating the mediating effect of bricolage in the relationship between data analytics capability and servitization. This leads to our first research question: *How does bricolage mediate the relationship between data analytics capability and servitization?*

Moreover, scholars claim that the efficacy of data analytics capability is conditional on organizational contextual factors (Dubey *et al.*, 2019; Suoniemi *et al.*, 2020). Despite the value of data analytics capability, the insights it yields can be highly innovative and revolutionary, to the extent it may be risky to implement in practice (Grover *et al.*, 2018). Manufacturers without an organizational culture that encourages innovation and risk-taking may hesitate and even refuse to leverage the insights obtained by data analytics to inform resource utilization. It is reported that the culture barrier is the main factor restricting organizations from realizing the value of data analytics (LaValle *et al.*, 2011). In this case, the effect of data analytics capability on servitization through bricolage may hinge on *innovation orientation*, the extent to which a manufacturer embraces a culture favoring creative ideas, experimentation, and risk-taking (Lee and Tang, 2018). Innovation-oriented manufacturers are open to exploring new technologies and experimenting with new ideas (Stock and Zacharias, 2011). They are more likely to experiment with the insights generated by data analytics capability to facilitate bricolage and ultimately servitization. However, the contingent role of innovation orientation in influencing the efficacy of data analytics capability in enabling servitization remains largely underexplored. This motivates our second research question: *How does innovation orientation moderate the effect of data analytics capability on servitization through bricolage?*

To answer our research questions, we draw on the dynamic capabilities theory (DCT), such that we model the mediation effect of bricolage in bridging the relationship between data analytics capability and servitization, as well as the moderating role of innovation orientation on the aforementioned mediation effect. Following past literature (e.g., Sousa and da Silveira, 2019; Visnjic *et al.*, 2019; Wang *et al.*, 2018), we categorize servitization into product-oriented and customer-oriented services to provide a nuanced understanding of the impact of data analytics capability on servitization. To examine the proposed hypotheses, we collected a matched dataset containing both archival data and multiple-respondent survey data from 1,206 top managers of 402 manufacturing firms in the Yangtze River Delta area in China. Because our research questions pertained to the mediating role of bricolage and the conditional effects of innovation orientation, we performed moderated mediation analyses to test the hypotheses. The results demonstrate that: (1) bricolage partially mediates the positive relationships between data analytics capability and product-oriented and customer-oriented services; and (2) the partial mediation effects of bricolage on the relationship between data analytics capability and product-oriented and customer-oriented services are stronger for manufacturers with higher innovation orientation.

This study contributes to the literature in three ways. First, we empirically reveal the direct effect of data analytics capability on servitization and provide confirmatory validation to prior studies that are based on conceptual and qualitative case studies. Second, we contribute to the literature by opening the black box of how data analytics capability influences servitization. This study reveals a critical underlying mechanism that converts data analytics capability into improved servitization by verifying the mediating effect of bricolage. Third, this research extends our understanding of the boundary condition that shapes the efficacy of data analytics capability in enabling servitization. By confirming the moderating role of innovation orientation, we delineate the conditions whereby data analytics capability has more or less effects on servitization through its impact on bricolage. Overall, by revealing the underlying mechanism and the boundary condition for this mechanism in the data analytics capability–servitization relationship, this study provides a nuanced understanding of how data analytics capability affects servitization.

2. Theoretical background and literature review

2.1 Dynamic capabilities theory

Extending the essentially static perspective of the resource-based view (RBV) of firms (Barney, 1991), dynamic capabilities theory (DCT) adopts a dynamic view and explains how organizations orchestrate resources to sustain competitive advantages in dynamic environments (Teece *et al.*, 1997). DCT emphasizes the value of organizational capabilities and distinguishes two types of capabilities: ordinary (zero-order) capabilities and dynamic capabilities (Winter, 2003). Ordinary capabilities are associated with basic functional activities that allow firms to make a living in the present. In contrast, dynamic capabilities enable firms to integrate, build, and reconfigure internal and external resources to address changing environments (Winter, 2003). With dynamic capabilities, firms can modify their resource bases, update ordinary capabilities, and initiate changes in external environments (Helfat and Winter, 2011). Dynamic capabilities are viewed as imperative for organizational success in rapidly changing environments (Ambrosini and Bowman, 2009).

The DCT literature further specifies a hierarchy of capabilities in which lower- and higher-order dynamic capabilities are intrinsically related (Collis, 1994; Winter, 2003). Lower-order dynamic capabilities refer to organizational routines that modify the current resource base, while higher-order dynamic capabilities refer to strategic routines that update resource bases through resource reconfiguration (Ambrosini and Bowman, 2009; Winter, 2003). Higher-order dynamic capabilities enable firms to continually create new competitive actions and sustain competitive advantages (Ambrosini and Bowman, 2009; Peteraf *et al.*, 2013). The literature further suggests that higher-order dynamic capabilities can be developed by leveraging lower-order dynamic capabilities (Teece, 2007). Further, lower-order dynamic capabilities also require higher-order dynamic ones to effectively affect business outcomes (Benitez *et al.*, 2018; Ciampi *et al.*, 2021; Teece, 2007).

Following the assertion on the hierarchy of capabilities in DCT (Teece, 2007), we posit that data analytics capability as a lower-order dynamic capability leads to servitization through developing a higher-order dynamic capability (i.e., bricolage). Data analytics capability facilitates a firm's understanding of its business and market and endows a firm with the ability to modify its current resource base to meet market changes (Chen *et al.*, 2015). Recent researchers have conceptualized data analytics capability as a lower-order dynamic capability that can be integrated to develop higher-order dynamic capabilities such as agility (Ghasemaghaei *et al.*, 2017), Logistic 4.0 capabilities (Bag *et al.*, 2020), and process-oriented dynamic capabilities (Wamba *et al.*, 2017). Meanwhile, bricolage resonates with the definition of higher-order dynamic capability because it allows a firm to recombine and reuse resources at hand to create novel resource combinations that update a firm's resource base (Baker and Nelson, 2005). Therefore, bricolage can be viewed as a higher-order dynamic capability that promotes business outcomes such as servitization. Following this logic, we propose that data analytics capability is a lower-order dynamic capability that can be leveraged to improve bricolage, a higher-order dynamic capability, which in turn affects servitization.

The DCT literature further posits that the process through which lower-order dynamic capabilities influence higher-order dynamic capabilities and business outcomes is highly context-specific (Schilke *et al.*, 2018). Recent researchers have recognized that this process often depends on organizational contexts such as organizational culture (Altay *et al.*, 2018; Cai *et al.*, 2019). Organizational culture captures a collection of shared values and beliefs within an organization (Liu *et al.*, 2010) and affects an organization's efforts in deploying dynamic capabilities (Altay *et al.*, 2018). In this vein, this research explores the contextual impact of organizational culture and posits that innovation orientation, as an important organizational culture (Lee and Tang, 2018), is likely to influence the effect of data analytics capability on servitization through bricolage.

In sum, DCT provides an appropriate theoretical framework to investigate our research model. Based on DCT, we first explore how bricolage, as a higher-order dynamic capability, mediates the relationship between data analytics capability and servitization. Moreover, we scrutinize the moderating role of innovation orientation in the aforementioned mediated relationship. Figure 1 presents our research model.

[Insert Figure 1 about here]

2.2 Servitization of manufacturing firms

Servitization refers to the addition of services to manufacturers' core product offerings to create new value for customers (Raddats *et al.*, 2019; Sousa and da Silveira, 2019). It enables manufacturers to bundle products and services into product-service combinations that satisfy customer needs and increase market differentiation (Raddats *et al.*, 2016). In the extant literature, researchers have widely recognized servitization as an effective way for manufacturers to improve customer satisfaction, increase total sales, and boost firm profitability (Visnjic *et al.*, 2016; Wang *et al.*, 2018). Manufacturers improve their servitization levels by extending the provision of services (Sousa and da Silveira, 2019). Hence, servitization studies normally use service offerings to reflect servitization and operationalize the degree of servitization through the extent of services offered by manufacturers (e.g., Sousa and da Silveira, 2019; Wang *et al.*, 2018; Zhou *et al.*, 2020). Besides, existing studies have widely categorized service offerings into product-oriented and customer-oriented services based on their levels of relatedness and interdependencies with current core products (Sousa and da Silveira, 2019; Visnjic *et al.*, 2019; Wang *et al.*, 2018).

Specifically, product-oriented services are performed to support basic product functionality (Visnjic *et al.*, 2019). Examples of product-oriented services include installation, provision of spare parts, monitoring, maintenance, and repairs (Wang *et al.*, 2018). These services are often standardized and involve limited customer interactions (Sousa and da Silveira, 2019), mainly requiring the support of products' technological resources such as engineering skills and product architecture knowledge (Visnjic *et al.*, 2019). By contrast, customer-oriented services go beyond product functionality to focus on supporting customers' product-related actions (Sousa and da Silveira, 2019). Examples include user training, product customization, consulting, and total solutions that include the aforementioned service components (Baines and Lightfoot, 2014). Customer-oriented services are often customized and involve close interactions with customers (Sousa and da Silveira, 2019). They require marketing and advanced technological resources (Visnjic *et al.*, 2019) such as specific service-process skills, technical knowledge of customers operations, and customer relational capital (Baines and Lightfoot, 2014). Following past studies (Visnjic *et al.*, 2019; Wang *et al.*, 2018), this research simultaneously investigates product-oriented and customer-oriented services to provide a comprehensive understanding of the impact of data analytics capability on servitization.

2.3 Data analytics capability and servitization

The immense potential of big data has attracted growing attention from manufacturers to develop a capability to analyze data for competitive advantages (Lehrer *et al.*, 2018). As the key to the effective use of analytics techniques to gain critical insights from big data, data analytics capability has quickly become imperative to business (Srinivasan and Swink, 2018). In general, data analytics capability refers to a firm's ability to use analytical tools and processes to analyze big data to derive insights for decision-making (Srinivasan and Swink, 2018). Data analytics capability captures the use of statistical techniques, data visualization techniques, and dashboards that aid in the organizational decision-making process (Srinivasan and Swink, 2018). It enables firms to attain and apply insights regarding multiple business functions (e.g., marketing, customer relationships, production) (Gupta *et al.*, 2020). Strategic decisions can be made based on these insights with a comprehensive understanding of organizational business processes and markets (Chen *et al.*, 2015; Ciampi *et al.*, 2021). Accordingly, data analytics capability has been highlighted as a critical capability for firm success (Ghasemaghaei *et al.*, 2017).

Recent research has started to investigate the role of data analytics in affecting servitization with statements on both opportunities and challenges (Opresnik and Taisch, 2015; Tronvoll *et al.*, 2020). Some scholars suggest the beneficial role of data analytics capability, which allows manufacturers to analyze big data associated with products, customers, and markets and to gain valuable insights to sense and seize servitization opportunities (Ardolino *et al.*, 2018; Opresnik and Taisch, 2015). For example, Opresnik and Taisch (2015) conceptually illustrated the value of big data strategies for servitization and posited that data analytics can generate insights on customer behaviors and demands for developing new services. The other school of thought suggests that data analytics incorporates emerging and sophisticated technologies with new complexities that may lead to failure in capturing their benefits (Brinch, 2018). In this case, the complexities associated with data analytics may produce unfavorable impacts on servitization (Tronvoll *et al.*, 2020).

These controversies suggest that data analytics capability is necessary but insufficient for manufacturers to turn the advantages of big data into service provisions, and it cannot be taken for granted that data analytics capability will automatically transfer into servitization (Coreynen *et al.*, 2017). Recent data analytics research posits that the power of data analytics capability in affecting business outcomes might be unleashed indirectly through a mediation mechanism of developing higher-order dynamic capabilities (Ciampi *et al.*, 2021; Mikalef *et al.*, 2020; Wamba *et al.*, 2017). Hence, an investigation of the underlying mediator that explains *how* data analytics capability affects servitization is a priority for both academics and practitioners (Ardolino *et al.*, 2018; Coreynen *et al.*, 2017).

However, the underlying mechanism of how data analytics capability affects servitization remains underexplored in current literature. Extant servitization studies have mainly emphasized the direct link between data analytics capability and servitization without offering much insight into the underlying mechanism (e.g., Ardolino *et al.*, 2018; Opresnik and Taisch, 2015). Failure to consider such an underlying mechanism is a critical research gap because it may constrain academics and practitioners from developing a comprehensive and generalized understanding of the business value of data analytics capability for servitization. Existing studies are mostly exploratory based on conceptual analysis or case studies (e.g., Ardolino *et al.*, 2018; Opresnik and Taisch, 2015) with a scarcity of quantitative investigation on how data analytics capability influences servitization. Therefore, there is a need for identifying and attesting to the underlying mechanism of the relationship between data analytics capability and servitization.

Researchers have increasingly acknowledged that the benefits of data analytics capability are not uniform across all firms but are contingent on organizational contexts (e.g., Dubey *et al.*, 2019; Suoniemi *et al.*, 2020). Organizational contexts favoring data analytics will catalyze the potential value of data analytics capability to a greater extent (Grover *et al.*, 2018). Recent studies have empirically revealed that the benefits of data analytics capability are contingent on social media diversity (Dong and Yang, 2020), business strategies (Suoniemi *et al.*, 2020), and organizational culture (Dubey *et al.*, 2019). These studies suggest that organizational contextual contingencies should be considered to offer a comprehensive understanding of how data analytics capability is transferred into servitization. Yet limited attention has been paid to possible contingencies that influence the effectiveness of data analytics capability in enabling servitization.

To summarize, according to the literature on the role of data analytics capability in servitization, two primary research gaps may inhibit an in-depth understanding of this topic. First, there is a lack of empirical research scrutinizing the underlying mechanism through which data analytics capability influences servitization. Second, although prior studies have alluded to potential boundary conditions that influence the effectiveness of data analytics capability in enabling servitization, there is a dearth of empirical investigations on these possible contingencies. Given these research gaps, the current study attempts to address them by investigating the mediating effect of bricolage in the relationship between data analytics capability and servitization as well as the moderating role of innovation orientation in the mediating effect. This research endeavors to provide a nuanced understanding of how data analytics capability influences servitization.

2.4 Bricolage

Bricolage refers to "making do by applying combinations of the resources at hand to new problems and opportunities" (Baker and Nelson, 2005, p. 333). It is a key capability for firms to address constraints in material, financial, and human resources (Busch and Barkema, 2021). Bricolage involves three core elements: (1) *making do* by proactively solving problems or capturing opportunities instead of pondering without taking any actions; (2) *utilizing resources at hand* rather than seeking new resources; and (3) *combining resources for new purposes* that go beyond the original intention or use (Baker and Nelson, 2005). Therefore, bricolage aligns with the definition of higher-order dynamic capabilities in DCT because it can stimulate novel resource combinations that update the current resource base of a firm (An *et al.*, 2018; Witell *et al.*, 2017).

Scholars have recently noticed the importance of bricolage to service development for service firms (Salunke *et al.*, 2013) and servitizing manufacturers (Witell *et al.*, 2017). Salunke *et al.* (2013) empirically reveal that bricolage enables service firms to manage resource constraints and develop supportive service innovation. Witell *et al.* (2017) conceptually analyze the significant role of bricolage in driving service development for servitizing manufacturers. Because service development may compete with tangible products for limited resources (Witell *et al.*, 2017), manufacturers aiming to servitize normally face resource constraints, encountering situations such as inadequate facilities, shortage of financial capital, and a lack of employees with service expertise (Kreye, 2017; Raja *et al.*, 2018). Bricolage could resolve this difficulty by enabling manufacturers to recombine and reuse the resources at hand in novel ways to create new opportunities for servitization. Notwithstanding these theoretical propositions, few studies have empirically investigated the role of bricolage in empowering servitization.

Despite the importance of bricolage in servitization, many manufacturers have found it difficult or challenging to develop bricolage because they do not have comprehensive knowledge of their existing resource base or lack the ability to explore creative ways to reuse existing resources (Sonenshein, 2014). This challenge could be resolved by leveraging data analytics capability, which could help firms increase organizational transparency on their resource base and extract insights for resource reuse to create business value (Chen *et al.*, 2015; Grover *et al.*, 2018). As such, the key to successful servitization is to leverage the power of data analytics capability to facilitate the development of bricolage, which is consistent with the hierarchy of capabilities suggested by DCT. Hence, this research proposes bricolage as the critical mediator that translates the advantages of data analytics capability into improved servitization.

3. Hypotheses development

3.1 Data analytic capability, bricolage, and servitization

Following the hierarchy of capabilities specified by DCT (Winter, 2003), we propose that data analytics capability represents a lower-order dynamic capability that can be leveraged to develop a higher-order dynamic capability (i.e., bricolage), which in turn improves servitization in terms of product-oriented and customer-oriented services. Data analytics capability improves bricolage by empowering manufacturers to fully understand existing resource bases and gain insights into resource recombination via large-scale data analysis (Chen *et al.*, 2015). With competencies in big data analytics, manufacturers can discern hidden patterns in operational processes and increase transparency regarding resource utilization (Brinch, 2018). This allows manufacturers to outline a complete picture of their resource base, which will facilitate the identification of underexplored resources (Kache and Seuring, 2017) and the deployment of these resources for new purposes. In this vein, data analytics capability promotes bricolage by enabling manufacturers to make full use of resources at hand.

In addition, data analytics capability can enhance bricolage by uncovering novel ways to recombine and reuse existing resources for new purposes. By taking advantage of data analytics, manufacturers can generate data-driven insights about the new connections among different resources and better understand the synergistic effects in existing resources (Chen *et al.*, 2015). This will formulate innovative or unconventional resource recombinations and facilitate the utilization of existing resources for purposes beyond the original intention (Grover *et al.*, 2018). Given this, we propose that data analytics capability has a positive effect on bricolage.

Improved bricolage, in turn, makes it possible for manufacturers to exploit the resources at hand to develop product-oriented and customer-oriented services. The offering of product-oriented and customer-oriented services often requires additional capabilities and resources that extend beyond manufacturers' current profile (Baines and Lightfoot, 2014; Kache and Seuring, 2017). As a higher-order dynamic capability, bricolage enables manufacturers to fill the resource gaps by recombining and reusing resources they already have (Witell *et al.*, 2017). For example, manufacturers can utilize existing technology stocks, expert technicians, and marketing experience to develop services that support product functionality and customer operations (Storey *et al.*, 2016). Hence, manufacturers with greater bricolage will be more flexible in developing and offering product-oriented and customer-oriented services because they are more capable of exploiting the potential of existing resources.

In addition, bricolage enables manufacturers to generate new knowledge that helps them sense and seize valuable servitization opportunities (Salunke *et al.*, 2013). With bricolage, manufacturers can acquire unexpected, tacit, and heterogeneous knowledge of recombining and reusing extant resources (Duymedjian and Rüling, 2010). Such knowledge enables manufacturers to reveal and seize unique product-oriented and customer-oriented services opportunities (Cunha *et al.*, 2014). For example, bricolage contributes to novel recombinations of manufacturing-based resources, such as specialized knowledge about product design and product/process engineering skills (Sousa and da Silveira, 2017). Manufacturers can use these recombinations to launch product-oriented services that require specific technological resources, like maintenance, provision of spare parts, and remote monitoring (Visnjic *et al.*, 2019). Bricolage also makes possible novel recombinations of deep knowledge in customer needs, usage patterns, and behaviors to develop services that support customer actions (Sousa and da Silveira, 2019). By recombining knowledge on customers with existing technology stocks, manufacturers can develop customer-oriented services, such as effective user training, product customization, and total solutions, that fulfill individualized customer needs (Sousa and da Silveira, 2017). As such, bricolage contributes to the development of both product-oriented and customer-oriented services.

Integrating the aforementioned arguments, we propose that bricolage mediates the influence of data analytics capability on servitization—i.e., data analytics capability enhances product-oriented and service-oriented services by facilitating greater bricolage. Consequently, we hypothesize that:

H1(a). Bricolage mediates the relationship between data analytics capability and product-orientated services.

H1(b). Bricolage mediates the relationship between data analytics capability and customer-orientated services.

3.2 Moderation role of innovation orientation

Following DCT, we posit that innovation orientation represents a critical contingent factor that shapes the effect of data analytics capability on servitization through bricolage. Innovation orientation is a form of organizational culture that encourages creative ideas, experimentation, and risk-taking (Lee and Tang, 2018). It emphasizes novelty and experimentation (Siguaw *et al.*, 2006), which aligns with the innovative nature of data analytics (Grover *et al.*, 2018). In this vein, innovation orientation affects a firm's motivation and efficiency to leverage data analytics. Hence, we expect that innovation orientation will influence the extent to which data analytics capability promotes bricolage and ultimately servitization.

Specifically, we argue that innovation orientation will enhance the effectiveness of data analytics capability in improving bricolage because it stimulates the experimentation of data-driven insights for resource recombination and reuse. Innovation-oriented manufacturers are prone to embracing new technologies and experimenting with new ideas (Wei *et al.*, 2013). As such, manufacturers with greater innovation orientation will devote significant efforts to using data analytics and experimenting with the insights derived from big data analytics. With such efforts, these manufacturers will utilize data analytics capability to a greater extent to detect underexplored resources and identify novel ways to recombine and reuse them for new purposes.

Innovation orientation also fosters a favorable organizational climate for risk-taking and the adoption of unconventional practices and ideas (Stock and Zacharias, 2011). Therefore, even though the insights about new resource combinations derived from data analytics may be unconventional with uncertainties, manufacturers with high innovation orientation will still be inclined to implement these insights to reconfigure resources to capture servitization opportunities. On the contrary, manufacturers with low levels of innovation orientation will be reluctant to implement these data-driven insights because they discourage uncertain and risky practices (Lee and Tang, 2018). Accordingly, innovation orientation will create an environment that motivates manufacturers to take full advantage of data analytics capability in improving bricolage. Improved bricolage, in turn, facilitates the recombination and reuse of resources at hand to develop product-oriented and customer-oriented services.

Overall, manufacturers will be more likely to leverage data analytics capability to develop greater bricolage to enhance product-oriented and customer-oriented services at higher levels of innovation orientation. Considering the mediation role of bricolage, we posit that innovation orientation will positively moderate the strength of the mediation effects of bricolage in the relationships between data analytics capability and product-oriented and customer-oriented services. Therefore, we develop the following hypotheses:

H2(a). Innovation orientation positively moderates the mediation effect of bricolage on the relationship between data analytics capability and product-oriented services.

H2(b). Innovation orientation positively moderates the mediation effect of bricolage on the relationship between data analytics capability and customer-oriented services.

4. Research methodology

4.1 Research design

To test our research model, we collected both archival and multiple-respondent survey data from manufacturers located in the Chinese Yangtze River Delta area, which is a global manufacturing hub with a high level of economic development (Liu *et al.*, 2016). Manufacturers in this area actively engage in digitalization and servitization activities to increase local and global competitiveness (Zhou *et al.*, 2021). Thus, the Yangtze River Delta area in China was a suitable empirical context for validating our research model.

Given the challenges of collecting data in China, we collaborated with a local administrative agency that oversaw local industrial development to obtain a representative sample. This agency compiled a list of 2,618 manufacturers to investigate local enterprise development for policy-making purposes. The agency provided us with the archival data of firms' contact and demographic information. This sample pool included manufacturers with diverse backgrounds in terms of firm size and age. The manufacturers in the sample also covered key manufacturing industries such as consumer products, petroleum and chemical, machinery, and electronics. Therefore, the diversity of the sampled manufacturers ensured the external validity of our study.

We employed survey-based subjective measures to collect data for our main constructs. Subjective measures are a well-documented and widely-accepted way of accurately capturing the picture of organization operations because the measures are standardized to facilitate comparison across organizations (Rai *et al.,* 2006). Furthermore, the use of subjective measures is highly recommended when the constructs under investigation could not be readily captured by objective data or when there are no relevant objective data available (Setia and Patel, 2013). Survey-based subjective measures have been used by a large number of researchers in operations management (e.g., Sousa and da Silveira, 2019; Srinivasan and Swink, 2018; Zhou *et al.*, 2020). To ensure the validity of the subjective measures, we developed a survey based on previously validated measures with good psychometric properties.

We conducted an online questionnaire survey in the autumn of 2020. We used a dominant online survey platform in China (*www.wjx.cn*), allowing respondents to click a link or scan a QR code to access the questionnaire. Before releasing the survey, the agency issued a formal invitation to solicit the voluntary participation of the firms. We then contacted and invited each firm's CEOs, marketing managers, and production managers to participate in our study voluntarily. In the cover letter of the questionnaire, we stated that responses would be confidential and only used for academic purposes. The respondents were prompted to specify their positions at the beginning of the survey, based on which they would be allocated questionnaire constructs that were relevant to their job positions. Marketing managers were directed to answer the questions regarding servitization because they are the most familiar with market-related issues. CEOs were directed to answer questions related to bricolage and innovation orientation given their in-depth understanding of the firms' resource statuses and overall cultural orientations. Production managers were directed to provide answers related to data analytics capability given their knowledge on the deployment of data analytics in the firms.

The multi-respondent approach ensured that each questionnaire construct was answered by the knowledgeable informant and the responses could accurately reflect the real-world phenomena (Van Bruggen *et al.*, 2002). Moreover, to precisely capture firms' demographic information (e.g., size, age, and industry), we incorporated related objective indicators from archival data. By combining multi-respondent survey data with archival data, our data collection approach not only reduced the threat of common method bias caused by the single-source respondent but also increased data validity (Shou *et al.*, 2016).

We made follow-up phone calls to encourage respondents to fill out the survey. In total, out of 2,618 firms listed by the agency, 758 manufacturers responded. After merging the questionnaires answered by CEOs, marketing managers, and production managers in each firm, we obtained complete data from 408 manufacturers. Among the 408 manufacturers, six were dropped because they did not provide any type of service offerings. The final sample included 1,206 respondents from 402 manufacturing firms, yielding a valid response rate of 15.36%.

Non-response bias was assessed after data collection. A *t*-test was conducted to compare the difference between the early (i.e., the first 15%) and late (i.e., the last 15%) responses in the manufacturers with complete questionnaires (Armstrong and Overton, 1977). No significant differences were observed between the two subsamples in terms of size ($t = 0.357$, $p = 0.722$), age ($t = -1.757$, $p = 0.082$), and industry type (χ^2 (4) = 6.908, $p = 0.141$). Moreover, we randomly selected 60 manufacturers from the 402 valid responses and 60 manufacturers who did not respond to our survey (Liu *et al.*, 2020). No significant difference was found between these two groups in terms of size ($t = -1.637$, $p = 0.102$), age ($t = -1.362$, $p = 0.174$), and industry type (χ^2 (4) = 4.764, $p = 0.312$). Hence, non-response bias was not a concern in our study. Table I presents the demographic information of our sample.

[Insert Table I about here]

4.2 Measures

We first developed an English-language questionnaire by adopting measures validated by previous studies. Because this study was conducted in China, we employed a back-translation approach for survey development (Hoskisson *et al.*, 2000). We hired a professional translator to translate the questionnaire into Chinese and then back-translate the Chinese version into English. The back-translated English version was checked against the original English version. After a careful discussion with the translator about the ambiguous wordings, we revised the Chinese version to ensure its accuracy and conceptual equivalence with the English version. We invited four experienced operations management scholars to review the questionnaire and provide feedback on question order and item wording. Based on their feedback, we further revised a few questionnaire items to improve clarity.

Next, we conducted a pilot test of the questionnaire with 30 managers who participated in an MBA program at a top university in China. These managers held senior positions in their companies and had abundant experience in the manufacturing industry. They also have adequate knowledge regarding information systems and operations management from attending the training courses in the MBA program. The relevant experience and knowledge background enabled them to provide valuable insights to improve our questionnaire. We invited these managers to answer the preliminary version of the survey and to provide suggestions about questionnaire items. According to their suggestions, we adapted items and clarified the wording to ensure content validity and the reliability of items in reflecting the real-world business contexts.

Consistent with existing studies (Kroh *et al.*, 2018; Sousa and da Silveira, 2019), s*ervitization* was measured as the extent of service provisions by manufacturers and was evaluated by marketing managers. Specifically, *product-oriented services* were measured with five items adapted from Sousa and da Silveira (2019) and Kroh *et al.* (2018). The items reflected services that support basic product functionality. *Customer-oriented services* were measured with five items adapted from Eggert *et al.* (2014) and Kroh *et al.* (2018). The items captured services that support customers' product-related actions. *Bricolage* was measured with seven items adapted from An *et al.* (2018) and evaluated by CEOs. These items captured a firm's ability to make do by recombining and reusing resources at hand for new purposes (Baker and Nelson, 2005). *Data analytics capability* was measured by three items originally developed by Srinivasan and Swink (2018) and assessed by production managers. The three items referred to the use of statistical techniques, data visualization techniques, and dashboards that aid in the organizational decision-making process. According to the suggestions of the managers participating in the pilot test, we removed two items in Srinivasan and Swink (2018) about data integration and deployment of dashboard to managers' communication devices from the final questionnaire because they were suggested to be less relevant to our emphasis on analytics of data for decision-making. *Innovation orientation* was measured with four items adopted from Lee and Tang (2018) and evaluated by CEOs. The items reflected the extent to which a firm is creative and receptive to new ideas and conceptual approaches.

We also controlled four variables that could potentially influence bricolage and servitization: *marketing capability*, *firm size*, *firm age*, and *industry*. Marketing capability refers to a firm's ability to identify customer needs and link with target customers (Zhou *et al.*, 2014). With a high level of marketing capability, manufacturers can understand resource requirements raised by new customer needs and effectively develop action plans to recombine resources at hand to satisfy these needs (Krasnikov and Jayachandran, 2008), which implies its potential influence on bricolage. Marketing capability also sheds light on customer needs on services and facilitates the development of services, thereby influencing the level of servitization (Storey *et al.*, 2016). Marketing capability was measured with four items adopted from Zhou *et al.* (2014) and was evaluated by marketing managers.

The effects of three typical firm demographic variables (i.e., firm size, firm age, and industry types) were also controlled (Su *et al.*, 2020; Zhou *et al.*, 2021). Smaller and younger manufacturers tend to have tight resource constraints and are more motivated to pursue bricolage than larger and older ones (Baker and Nelson, 2005). Given their resource constraints, smaller and younger manufacturers are less likely to invest in service development and improve the level of servitization (Santamaría *et al.*, 2012). Accordingly, we controlled the influence of firm size and firm age on bricolage and servitization. Firm size was measured using the natural logarithm of the number of employees and firm age was measured using the natural logarithm of operating years. We also controlled for industry types because manufacturers from different industries may vary in terms of the level of bricolage (Su *et al.*, 2020) and the implementation of servitization (Wang *et al.*, 2018). We included four industry dummies (see Table I) with *other industries* as the baseline. Firm age, size, and industry type were measured using archival data provided by the agency.

4.3 Reliability and validity

We employed confirmatory factor analysis to evaluate construct reliability and validity (see Appendix A). The results revealed that the data fit the model well (χ^2/df = 948.268/335 = 2.831; comparative fit index (CFI) = 0.934; Tucker–Lewis index (TLI) = 0.926; root mean square error of approximation (RMSEA) = 0.067). In addition, the values of Cronbach's α and composite reliability all exceeded 0.70, indicating good reliability (Hair *et al.*, 2010). All standard factor loadings were significant and greater than 0.60. The average variance extracted (AVE) values ranged from 0.540 to 0.840 and were above the 0.50 cutoff (Hildebrandt, 1987), suggesting adequate convergent validity.

Moreover, the results shown in Table II demonstrate that the square roots of the AVEs for each construct were greater than the correlations between constructs, suggesting satisfactory discriminant validity (Fornell and Larcker, 1981). To address multicollinearity issues, variance inflation factor (VIF) values were computed for variables (Hair *et al.*, 2010). The results showed that the VIF values ranged from 1.12 to 1.89 with a mean of 1.50, indicating multicollinearity was not a serious concern in this study. Finally, we employed both procedural and statistical remedies to mitigate possible common method bias. The details can be found in Appendix B.

[Insert Table II about here]

5. Analyses and results

The basic descriptive analysis for variables is presented in Table II. It shows the means and standard deviations of variables as well as inter-variable correlations. The correlation coefficients show that data analytics capability relates positively to bricolage (r = 0.271, p < 0.001), product-oriented services (r = 0.240, p < 0.001), customer-oriented services (r = 0.337, p < 0.001), and innovation orientation (r = 0.24, p < 0.001). Bricolage is positively related to product-oriented services (r = 0.231, p < 0.001) and customer-oriented services (r = 0.340, p < 0.001). These results provide initial evidence to our hypotheses.

The PROCESS macro (version 3.5) was employed to test the hypotheses (Hayes, 2017). The PROCESS analysis invokes a powerful bootstrapping method to test the statistical significance of indirect effects in mediation and moderated mediation models (Gerpott *et al.*, 2019; Prajogo *et al.*, 2021). The basic requirement for a significant indirect effect is that the 95% confidence intervals (CIs) do not contain zero (with 5,000 bootstrapping resamples) (Hayes, 2017).

5.1 Mediation effects

H1a and H1b posit that bricolage mediates the effect of data analytics capability on (a) product-oriented services and (b) customer-oriented services. Because these hypotheses focus on bricolage's mediation effect, we followed Hayes's (2017) guidelines and employed "Model 4" in PROCESS to test the model. The results of the step-by-step analysis presented in Table III show that data analytics capability is positively associated with bricolage ($\beta = 0.111$, $SE = 0.026$, $p < 0.001$), and bricolage is positively related to both product-oriented services ($\beta = 0.249$, $SE = 0.113$, $p < 0.05$) and customer-oriented services ($\beta = 0.250$, $SE = 0.068$, $p < 0.001$). Additionally, bootstrapping with 5,000 resamples was executed to test the significance of the direct and indirect effects of data analytics capability on product-oriented and customer-oriented services. The results showed that the direct effects of data analytics capability on product-oriented services (direct effect = 0.266, SE = 0.060, 95% CI: 0.149–0.383) and customer-oriented services (direct effect = 0.176, SE = 0.036, 95% CI: 0.106–0.246) are significant. The results further revealed significant indirect effects of data analytics capability on product-oriented services (indirect effect = 0.028, SE = 0.016, 95% CI:

0.004–0.065) and customer-oriented services (indirect effect = 0.028, *SE* = 0.012, 95% CI: 0.008–0.054) through bricolage. Both direct and indirect effects of data analytics capability on product-oriented and customer-oriented services are thus significantly positive, indicating partial mediation effects of bricolage. As such, both H1a and H1b are supported. Figure 2 depicts the results of the mediation analysis.

[Insert Table III about here]

[Insert Figure 2 about here]

5.2 Moderated mediation effects

H2a and H2b hypothesize that innovation orientation would positively moderate the indirect effect of data analytics capability on (a) product-oriented services and (b) customer-oriented services through bricolage. Because these two hypotheses propose moderated-mediation effects of innovation orientation, they were tested using “Model 7” in PROCESS (Hayes, 2017). Following recommended practices (Paillé *et al.*, 2019), the variables were mean-centered to avoid potential multicollinearity issues. The results are depicted in Table IV. The coefficient of the interaction term between data analytics capability and innovation orientation for bricolage is significantly positive ($\beta = 0.099$, $SE = 0.027$, $p < 0.001$), indicating a positive moderation effect of innovation orientation. Figure 3 depicts the marginal effects of data analytics capability on bricolage at varying levels of innovation orientation.

[Insert Figure 3 about here]

[Insert Table IV about here]

Specifically, the results show that the indirect effects of data analytics capability on product-oriented and customer-oriented services through bricolage vary at different levels of innovation orientation. The indirect effect of data analytics capability on product-oriented services through bricolage is not significant at low levels of innovation orientation (indirect effect = −0.004, SE = 0.008, 95% CI: −0.017–0.015) but becomes significant at high levels of innovation orientation (β = 0.025, *SE* = 0.012, 95% CI 0.006–0.051). Furthermore, the difference between the indirect effects at low and high levels of innovation orientation is 0.029 and significant (SE = 0.013, 95% CI: 0.005–0.055). The moderated mediation index for product-oriented services is 0.025, and the 95% CI does not include zero (SE = 0.011, 95% CI: 0.004–0.047). These results indicate that the indirect effect of data analytics capability on product-oriented services through bricolage changes from non-significant to significant when the level of innovation orientation increases from low to high. Jointly with the significant difference of indirect effects at low and high levels of innovation orientation, it is confirmed that the indirect effect of data analytics capability on product-oriented services through bricolage is positively moderated by innovation orientation, which supports H2a.

Similarly, the results show that the indirect effect of data analytics capability on customer-oriented services through bricolage is not significant when innovation orientation is low (β = −0.004, *SE* = 0.007, 95% CI: −0.016–0.013) but turns to be significant at high levels of innovation orientation (β = 0.025, *SE* = 0.009, 95% CI: 0.010–0.045). The difference between them is 0.029 and significant (SE = 0.011, 95% CI: 0.008–0.051). Additionally, the moderated mediation index is positive and significant (β =0.025, SE = 0.009, 95% CI 0.007–0.043). As innovation orientation increases from low levels to high levels, the indirect effect of data analytics capability changes from non-significant to significant with a significant difference in the coefficients. Given this, the indirect effect of data analytics capability on customer-oriented service through bricolage is positively moderated by innovation orientation, confirming H2b.

5.3 Post hoc analyses

Three *post hoc* analyses were conducted to provide additional insights on the relationships among data analytics capability, bricolage, innovation orientation, and servitization. The results can be found in Appendix C. First, because data analytics capability directly affects servitization, innovation-oriented manufacturers are more likely to turn the insights generated from data analytics capability into servitization. Accordingly, we examined the moderation effect of innovation orientation on the data analytics capability–servitization relationship. However, our results showed that for the coefficients of the interaction terms between data analytics capability and innovation orientation for product-oriented services (β = 0.034, SE = 0.086, p = 0.688) and customer-oriented services (β = 0.027, SE = 0.051, p = 0.603), neither is significant (Model 3 and 4 in Table C I, Appendix C). These findings imply that manufacturers can glean the benefits of data analytics capability in servitization regardless of their innovation orientation. Together with the results from moderated mediation analysis, we find that innovation orientation significantly moderates the indirect effect of data analytics capability on servitization through bricolage but does not significantly moderate its direct effect on servitization. These findings attest to our assertion that the moderation effect of innovation orientation in the relationship between data analytics capability and servitization mainly attributes to its critical role in amplifying the efficacy of data analytics capability on bricolage. In other words, given the mediation effect of bricolage, an increase in innovation orientation can lead to greater servitization because it strengthens the effect of data analytics capability on bricolage.

Second, as innovation-oriented manufacturers creatively leverage bricolage to provide service offerings, the effect of bricolage on servitization might be moderated by innovation orientation. The empirical results of this study suggest the coefficient of the interaction term between innovation orientation and bricolage is significant for product-oriented services (β = 0.216, SE = 0.099, $p < 0.05$) and customer-oriented services (β = 0.126, SE = 0.059, $p < 0.005$) (Model 3 and 4 in Table C II, Appendix C). In this sense, innovation-oriented manufacturers are more likely to exploit the value of bricolage for servitization.

Third, based on the aforementioned analysis, we further explored whether innovation orientation moderates the mediation effect of bricolage via the bricolage–servitization relationship. We selected "Model 14" in PROCESS to test this type of moderated mediation effect. The results show that the moderated mediation index is not significant for either product-oriented services (β = 0.015, SE = 0.018, 95% CI: −0.002–0.068) or customer-oriented services (β = 0.008, SE = 0.008, 95% CI: −0.009–0.027) (Table C III, Appendix C). This further supports our proposal that an increase in innovation orientation will strengthen the effect of data analytics capability on servitization by yielding a greater level of bricolage.

6. Discussion and implications

Despite anecdotal evidence on the importance of data analytics capability to servitization, empirical investigation on how data analytics capability influences servitization remains scant. Drawing upon DCT, this research proposes a moderated mediation model which posits the mediation effect of bricolage on the relationship between data analytics capability and servitization as well as the moderating effect of innovation orientation on this mediation effect. Using both archival data and multiple-respondent survey data from 1,206 top managers of 402 manufacturing firms, the results support the theoretically-derived research model and offer two critical findings.

First, the results show that bricolage partially mediates the relationship between data analytics capability and servitization, which reveals that data analytics capability affects servitization both directly and indirectly through bricolage. On one hand, the direct effect of data analytics capability on servitization lends empirical support to the past literature asserting that data analytics capability affects servitization directly (e.g., Opresnik and Taisch, 2015). This finding is consistent with DCT literature that suggests lower-order dynamic capabilities can also directly generate value for firms (Ciampi *et al.*, 2021; Winter, 2003).

On the other hand, the mediation test confirms the partial mediation effect of bricolage, which suggests that bricolage is an important bridge connecting data analytics capability and servitization. This finding echoes recent studies, which call for a nuanced understanding of how data analytics capability influences servitization (Ardolino *et al.*, 2018; Coreynen *et al.*, 2017). Our study also confirms the importance of exploiting bricolage to recombine and reuse existing resources for servitization (Witell *et al.*, 2017), which extends the empirical work of Salunke *et al.* (2013) to the manufacturing context. Consistent with the hierarchy of capabilities in DCT (Schilke *et al.*, 2018; Winter, 2003), our findings suggest that the impact of data analytics capability, as a lower-order dynamic capability, on business outcomes are mediated by related higher-order dynamic capabilities (e.g., Ciampi *et al.*, 2021; Mikalef *et al.*, 2019; Wamba *et al.*, 2017). However, the partial mediation effect implies that data analytics capability may affect servitization through factors other than bricolage, which merits further exploration in future studies.

Second, our finding on the moderated mediation effect indicates that innovation orientation strengthens the indirect effect of data analytics capability on servitization through bricolage. Existing research suggests careful consideration of boundary conditions of leveraging data analytics capability to attain a comprehensive understanding of its value (e.g., Grover *et al.*, 2018; Suoniemi *et al.*, 2020). Our finding resonates with this research stream by validating the critical role of innovation orientation in invigorating the value of data analytics capability on bricolage and servitization. In addition, our finding is consistent with DCT literature, which contends that the influence of lower-order dynamic capabilities on higher-order dynamic capabilities and business outcomes depends on organizational contexts (Schilke *et al.*, 2018). Overall, the findings of this research provide valuable insights for understanding the influence of data analytics capability on improving servitization.

6.1 Theoretical implications

This study has important implications for existing literature. First, it contributes to the servitization literature by providing empirical evidence for the critical role of data analytics capability for servitization. Existing servitization studies have explored the influence of data analytics capability on servitization based on exploratory conceptual analysis or qualitative case studies (Ardolino *et al.*, 2018; Opresnik and Taisch, 2015), whose findings need confirmatory validation from a relatively large-scale dataset (Chen *et al.*, 2021). However, to date, there have been few studies providing empirical evidence. The current study bridges the research gap by empirically verifying the positive impact of data analytics capability on servitization with quantitative data collected from more than 400 manufacturers in different manufacturing industries.

Second, this study opens the black box of how data analytics capability affects servitization by attesting to the mediating mechanism of bricolage. Although existing literature has called for empirical investigations to unravel the underlying mechanism that explains how the value of data analytics is transferred to servitization (Coreynen *et al.*, 2017), related research remains scarce. According to the hierarchy of capabilities in DCT (Schilke *et al.*, 2018; Winter, 2003), we posit and find that data analytics capability, as a lower-order dynamic capability, empowers servitization by enhancing bricolage, a higher-order dynamic capability. Bricolage facilitates the provision of services by enabling manufacturers to tackle resource constraints through recombining and reusing existing resources (Witell *et al.*, 2017). Hence, this study extends current research by empirically elucidating bricolage as an effective mechanism for manufacturers to transform the value of data analytics capability into enhanced servitization.

Third, our finding reveals innovation orientation as a contingent factor influencing the mechanism through which data analytics capability drives servitization. Although recent studies suggest the efficacy of data analytics capability is highly context-specific (e.g., Dubey *et al.*, 2019; Suoniemi *et al.*, 2020), few researchers have examined the contingent factors that influence the efficacy of data analytics capability in enabling servitization. Our research fills this gap by validating that innovation orientation acts as a boundary condition for bricolage to mediate the relationship between data analytics capability and servitization. Our research also extends DCT literature (Schilke *et al.*, 2018) by revealing that innovation orientation is a critical contingent factor of the hierarchy of capabilities for servitization. In sum, by revealing the underlying mechanism and the boundary condition for this mechanism in the data analytics capability–servitization relationship, this study provides a nuanced understanding of how data analytics capability affects servitization.

6.2 Managerial implications

Our findings also offer important practical implications for manufacturers aiming to transform from pure product producers to service providers. First, this study reminds manufacturers to invest in building data analytics capability to unleash the power of big data to improve the extent of servitization. The proliferation of big data has offered manufacturers comprehensive information about customer behaviors and preferences (Ciampi *et al.*, 2021). Manufacturers could exploit the value of big data by developing data analytics capabilities to identify customer needs on service provisions and generate insights to offer services tailored to customer expectations (Opresnik and Taisch, 2015).

Second, manufacturers are advised to extend the application of data analytics to resource utilization and develop the capability of bricolage for servitization. Our findings validate that bricolage is a critical channel through which data analytics capability promotes servitization. When manufacturers are faced with resource constraints in the provision of services, they can leverage their data analytics capabilities to increase transparency on current resource bases and generate insights to improve the ability of bricolage in terms of recombining resources at hand for new uses. With improved bricolage, manufacturers can enhance servitization by recombining their existing resources, such as product design knowledge, process engineering skills, and customer behaviors information, to develop services that support product functionality and customer operations (Sousa and da Silveira, 2017). Hence, manufacturers should channel the insights afforded by data analytics capability into improving bricolage to make full use of existing resources for servitization.

Third, manufacturers are encouraged to foster a culture of innovation orientation to amplify the benefits of data analytics in servitization. An organizational culture that aligns with data analytics practices often strengthens the efficacy of harnessing data analytics capability (Dubey *et al.*, 2019). Our findings suggest that manufacturers with greater innovation orientation will derive additional value from data analytics capability to facilitate the provision of services through bricolage. In this sense, senior managers can communicate the value of innovation across their firms and promote a culture oriented toward innovation. To the extent that manufacturers develop innovation orientation, their competence to deploy insights generated from data analytics in bricolage and servitization will increase significantly.

6.3 Limitations and future research

Although this study productively expands servitization scholarship, it has limitations that could be addressed in future research. First, recognizing manufacturers' resource constraints for servitization, this study focuses primarily on the mediating role of bricolage to understand how data analytics capability affects servitization. Future researchers could build on our research to explore other possible mediators, such as knowledge management and information sharing, that may mediate the effect of data analytics capability on servitization.

Second, we conducted this study with data collected from the Yangtze River Delta area in China because the manufacturers in this area have been striving to improve servitization for competitiveness. Although the context of sampling aligns with our research purpose, the Chinese Yangtze River Delta context may to some extent, limit the generalizability of findings to other areas, especially Western countries (Li and Tang, 2010; Xie, 1996). However, our results did provide considerable support to DCT and presented consistent findings with existing case studies conducted in the Western contexts (e.g., Ardolino *et al.*, 2018; Coreynen *et al.*, 2017). This implies that servitization patterns might be similar for manufacturers in our sample and the Western countries. Future researchers could collect data from Western countries to improve the generalizability of our findings.

Third, because of the difficulty of collecting archival data on firm-level variables such as data analytics capability and servitization, we employed previously validated survey measures to operationalize related constructs. Future researchers might consider using secondary data collected from firm archival files to operationalize variables with objective measures to validate this study's results. These limitations notwithstanding, this study provides novel insights into how data analytics capability influences servitization and offers critical implications for research and practice.

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Tables

Table I.

Sample profile (N=402)

Characteristics		Obs	Percent (%)
Manufacturing Industry	Consumer products	81	20.149
	Petroleum and chemical	77	19.154
	Machinery	107	26.617
	Electronics	88	21.891
	Others (e.g., metal and non-metallic mineral products)	49	12.189
Firm age (years)	<= 5	8	1.990
	6-10	109	27.114
	11-15	133	33.085
	16-20	106	26.368
	>= 21	46	11.443
Number of employees	<=50	87	21.642
	51-100	106	26.368
	101-200	104	25.871
	201-300	36	8.955
	>300	69	17.164

Table II.

Correlation matrix, means, and standard deviations.

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1. Product-oriented services	**0.860**	0.549***	0.216***	0.225***	0.144**	0.143**	−0.019	−0.082	−0.017	−0.255***	−0.252***	0.254***
2. Customer-oriented services	0.558***	**0.797**	0.327***	0.324***	0.284***	0.413***	0.007	−0.089	−0.041	−0.085	−0.085	0.100*
3. Bricolage	0.231***	0.340***	**0.859**	0.257***	0.726***	0.274***	0.103*	−0.062	−0.067	−0.018	−0.098*	0.075
4. Data analytics capability	0.240***	0.337***	0.271***	**0.917**	0.233***	0.229***	0.113*	−0.174***	0.001	0.037	−0.009	−0.024
5. Innovation orientation	0.160**	0.298***	0.731***	0.248***	**0.841**	0.236***	0.030	−0.093	−0.024	0.024	−0.050	0.007
6. Marketing capability	0.159**	0.424***	0.288***	0.244***	0.251***	**0.735**	0.090	−0.101*	0.003	0.181***	−0.041	−0.128**
7. Firm size (ln)	−0.000	0.026	0.120*	0.130**	0.048	0.107*	**n.a.**	0.179***	−0.098*	0.052	−0.098*	0.058
8. Firm age (ln)	−0.061	−0.068	−0.042	−0.152**	−0.072	−0.080	0.195***	**n.a.**	−0.113*	−0.090	0.098	−0.036
9. Consumer products [a]	0.002	−0.021	−0.047	0.020	−0.005	0.022	−0.077	−0.092	**n.a.**	−0.210***	−0.204***	−0.248***
10. Petroleum and chemical [a]	−0.231***	−0.064	0.001	0.055	0.043	0.197***	0.070	−0.069	−0.187***	**n.a.**	−0.269***	−0.328***
11. Machinery [a]	−0.228***	−0.064	−0.077	0.010	−0.030	−0.021	−0.077	0.115*	−0.181***	−0.245***	**n.a.**	−0.318***
12. Electronics [a]	0.268***	0.117*	0.093	−0.005	0.026	−0.107*	0.076	−0.016	−0.224***	−0.303***	−0.293***	**n.a.**
13. Restaurant preference [b]	0.150**	0.267***	0.239***	0.253***	0.154**	0.206***	0.033	−0.109*	0.052	0.019	0.066	−0.086
Mean	4.175	4.730	4.246	3.326	4.274	3.831	4.715	2.575	0.122	0.201	0.192	0.267
SD	1.291	0.795	0.535	1.009	0.587	0.605	0.978	0.401	0.328	0.402	0.394	0.443

Note: Elements along diagonal (in bold) are square roots of AVE. [a] Dummy variable with *other industries* as the baseline. [b] Restaurant preference is a marker variable to test common method bias (see Appendix B for details). Unadjusted correlations appear below the diagonal; correlations adjusted for the common method appear above the diagonal (see Appendix B for details). * $p < 0.05$, ** $p < 0.01$, *** $p<0.001$.

Table III.

Regression on bricolage, product-oriented and customer-oriented services, and bootstrapping analysis for indirect effects.

	Model 1		Model 2		Model 3	
	Bricolage		Product-oriented services		Customer-oriented services	
Regression results	Coefficients	SE	Coefficients	SE	Coefficients	SE
Bricolage			0.249*	0.113	0.250***	0.068
Data analytics capability (DAC)	0.111***	0.026	0.266***	0.060	0.176***	0.036
Marketing capability	0.224***	0.043	0.336***	0.101	0.481***	0.060
Firm size	0.031	0.027	−0.093	0.060	−0.056	0.036
Firm age	−0.004	0.065	0.012	0.147	0.019	0.088
Consumer products [a]	−0.121	0.089	−0.452*	0.201	−0.147	0.120
Petroleum and chemical [a]	−0.113	0.078	−1.121***	0.176	−0.308**	0.105
Machinery [a]	−0.120	0.078	−1.028***	0.176	−0.167	0.105
Electronics [a]	0.059	0.072	0.169	0.162	0.111	0.097
R^2	0.151		0.266		0.309	
F value	8.727		15.767		19.468	

Direct effect

	Direct effect	SE	95% CI
DAC→Product-oriented services	0.266	0.060	[0.149, 0.383]
DAC→Customer-oriented services	0.176	0.036	[0.106, 0.246]

Indirect effect (bootstrapping analysis)

	Indirect effect	Boot SE	95% Boot CI
DAC→ Bricolage→Product-oriented services (**H1**)	0.028	0.016	[0.004, 0.065]
DAC→ Bricolage→Customer-oriented services (**H2**)	0.028	0.012	[0.008, 0.054]

Note: * $p < 0.05$, ** $p < 0.01$, *** $p<0.001$. [a] Dummy variable. SE = standard error; CI = confidence interval.

Table IV

Regression on bricolage, moderation effect of innovation orientation and bootstrapping analysis for conditional indirect effects.

		Model 4		
		Bricolage		
Regression results		Coefficients	SE	
Data analytics capability (DAC)		0.043*	0.019	
Innovation orientation		0.615***	0.031	
DAC×Innovation orientation		0.099***	0.027	
Marketing capability		0.087**	0.031	
Firm size		0.028	0.019	
Firm age		0.035	0.046	
Consumer products [a]		−0.087	0.063	
Petroleum and chemical [a]		−0.094	0.055	
Machinery [a]		−0.089	0.055	
Electronics [a]		0.036	0.051	
R^2		0.584		
F value		54.908		
Conditional indirect effect (bootstrapping analysis)				
	Moderator (Innovation orientation)	Indirect effect	Boot SE	95% Boot CI
DAC→Bricolage→Product-oriented services	Low (−1 SD)	−0.004	0.008	[−0.017, 0.015]
	High (+1 SD)	0.025	0.012	[0.006, 0.051]
	Difference	0.029	0.013	[0.005, 0.055]
DAC→Bricolage→Customer-oriented services	Low (−1 SD)	−0.004	0.007	[−0.016, 0.013]
	High (+1 SD)	0.025	0.009	[0.010, 0.045]
	Difference	0.029	0.011	[0.008, 0.051]
Index of moderated mediation bootstrapping analysis				
		Index	Boot SE	95% Boot CI
H2a		0.025	0.011	[0.004, 0.047]
H2b		0.025	0.009	[0.007, 0.043]

Note: * $p < 0.05$, ** $p < 0.01$, *** $p<0.001$. [a] Dummy variable. SE = standard error; CI = confidence interval.

Figures

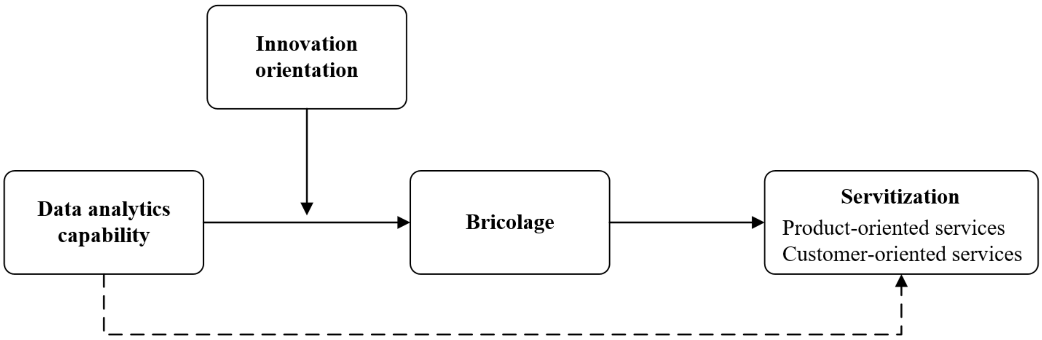
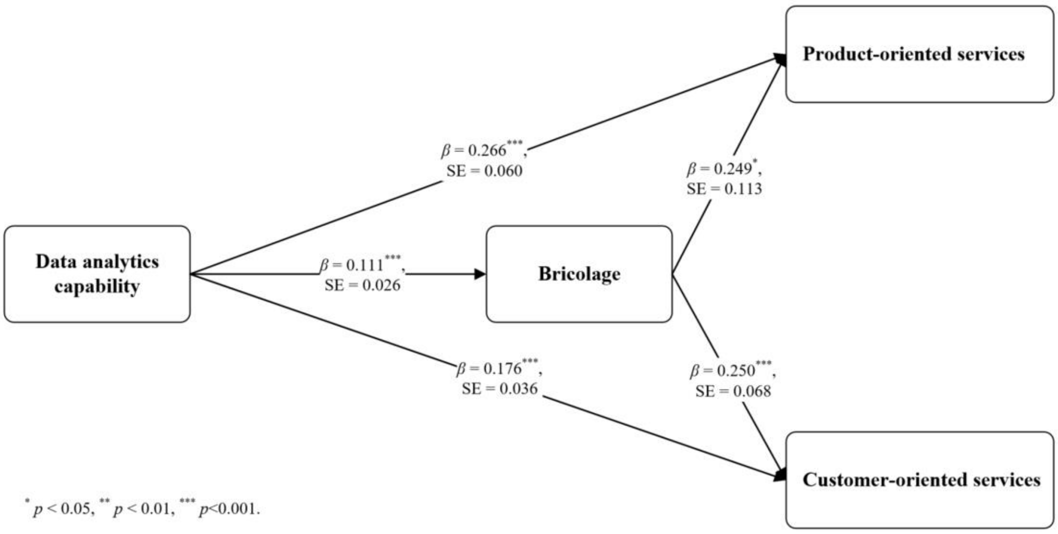
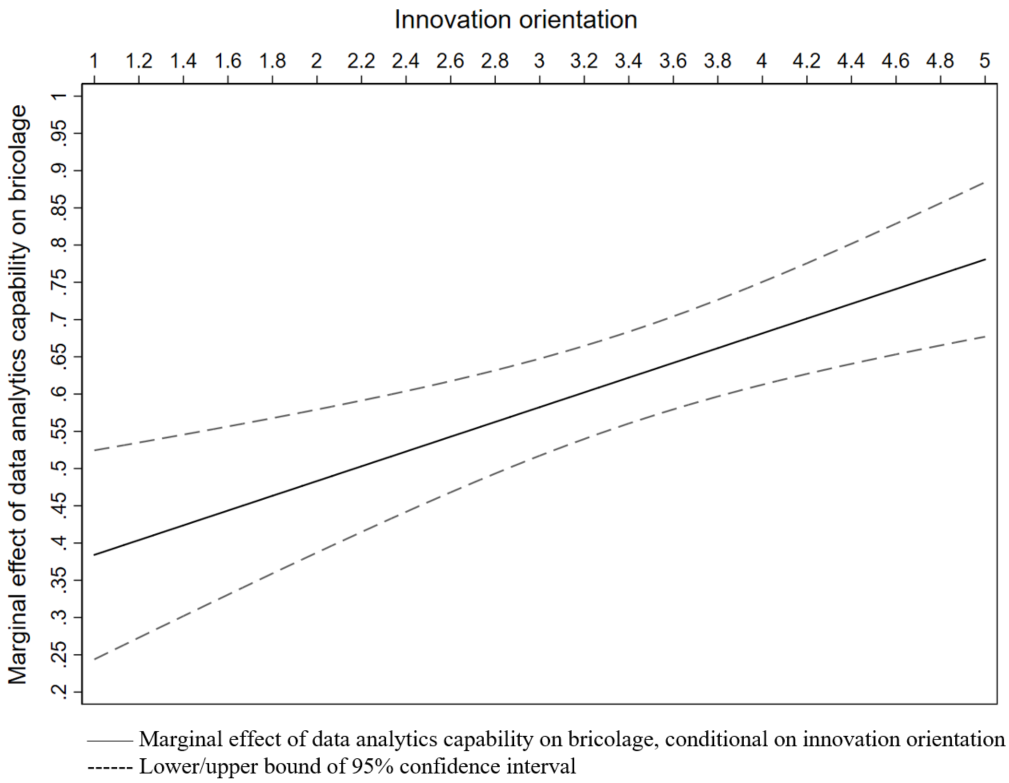


Figure 1 Research model



Indirect effect of data analytics capability on product-oriented services = 0.028, SE = 0.016, 95% CI: 0.004, 0.065
Indirect effect of data analytics capability on customer-oriented services = 0.028, SE = 0.012, 95% CI: 0.008, 0.054

Figure 2 Mediation effect of bricolage



Note: The y-axis denotes the marginal effect of data analytics capability on bricolage, while the x-axis represents the levels of innovation orientation. The dotted lines show the CI bound (95% level, two-tailed). If the CI is entirely on one side of the horizontal zero line, the marginal effect of data analytics capability on bricolage is significant at the given value of innovation orientation.

Figure 3. Interaction effects

Appendix A.

Measures

Constructs and measures	SFL	Source	Respondents
Product-oriented services (CR=0.934, AVE=0.739, α=0.933)		Sousa and da Silveira (2019) and Kroh *et al.* (2018)	Marketing manager
To what extent are the following services offered? (A six-point scale from 1 “none”, 2 “low” to 6 “high”)			
1. Spare parts supply	0.798		
2. Inspection/maintenance/repairs	0.888		
3. Assembly/installation/implementation	0.885		
4. Teleservice and remote service (condition monitoring)	0.858		
5. Preventative maintenance	0.866		
Customer-oriented services (CR=0.897, AVE=0.636, α=0.894)		Eggert *et al.* (2014) and Kroh *et al.* (2018)	Marketing manager
To what extent are the following services offered? (A six-point scale from 1 “none”, 2 “low” to 6 “high”)			
1. Technical user training	0.772		
2. Customized research and development	0.727		
3. Operating optimization	0.827		
4. Total solutions	0.923		
5. Analysis of operating data	0.721		
Bricolage (CR=0.952, AVE=0.738, α=0.952)		An *et al.* (2018)	CEO
To what extent you agree with the following statements. (A five-point scale from 1 “strongly disagree” to 5 “strongly agree”)			
1. We are confident of our ability to find workable solutions to new challenges by using our existing resources	0.814		
2. We gladly take on a broader range of challenges than others with our resources	0.818		
3. We use any existing resource that seems useful to respond to a new problem or opportunity	0.833		
4. When dealing with new problems or opportunities we take action by assuming that we will find a workable solution	0.873		
5. By combining our existing resources, we take on a surprising variety of new challenges	0.905		
6. When we face new challenges we put together workable solutions from our existing resources	0.900		
7. We combine resources to accomplish new challenges that the resources were not originally intended to accomplish	0.866		
Data analytics capability (CR=0.940, AVE=0.840, α=0.939)		Srinivasan and Swink (2018)	Production manager
To what extent you agree with the following statements. (A five-point scale from 1 “strongly disagree” to 5 “strongly agree”)			
1. We use advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision making	0.848		
2. We routinely use data visualization techniques (e.g., dashboards) to assist users or decision-makers in understanding complex information	0.945		

3. Our dashboards give us the ability to decompose information to help root cause analysis and continuous improvement	0.952		
Innovation orientation (CR=0.906, AVE=0.707, α=0.905)		Lee and Tang (2018)	CEO
Please use the following scale from 1 “weak emphasis” to 5 “strong emphasis” in response to the following statements.			
1. Creating revolutionary new conceptual approaches	0.845		
2. Experimenting with radical new works	0.883		
3. Challenging traditional product boundaries	0.851		
4. Increasing the firm’s overall commitment to develop and market new products	0.780		
Marketing capability (CR=0.823, AVE=0.540, α=0.811)		Zhou *et al.* (2014)	Marketing manager
Please tell us to what extent you agree with the following statements. (A five-point scale from 1 “strongly disagree” to 5 “strongly agree”)			
1. We devote substantial resources to understanding customer needs	0.809		
2. All of our business functions are integrated in serving the needs of our target market	0.793		
3. We frequently launch new advertising campaigns to promote our products	0.618		
4. We have extensive distribution channel coverage to make our products widely available	0.704		
Restaurant preference (Marker variable) (CR=0.899, AVE=0.750, α=0.894)		Gupta *et al.* (2007)	Production manager
Please tell us the degree to which the following aspects will affect your preference for a restaurant. (A five-point scale from 1 “low” to 5 “high)			
1. The friendliness of service personnel	0.740		
2. The availability of healthy meals	0.900		
3. The cleanliness of the place	0.944		

Notes: SFL= standardized factor loading; CR = composite reliability; AVE = average variance extracted; α = Cronbach’s alpha.

Appendix B.

Common Method Bias

To reduce common method bias, four procedural remedies were implemented in the research design and data collection stages (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). First, the questionnaire was carefully elaborated to reduce item ambiguity and divided conceptual adjacent constructs into different pages. Second, respondents' voluntary participation was confirmed, and their anonymity was protected to reduce the likelihood of socially desirable responses. Third, three respondents (e.g., CEO, marketing manager, and production manager) from each firm were invited to answer questionnaires. Finally, archival and multiple-respondent survey data were combined to test the research model.

Furthermore, common method bias was evaluated using two statistical methods. First, Harman's one-factor test revealed the fit indices of the measurement model were considerably better than those of the one-factor model (χ^2/df = 5585.957/350 = 15.960; CFI = 0.440; TLI = 0.395; RMSEA = 0.193). Second, we employed a method variance (MV) marker, *restaurant preference* of production managers to assess common method bias (Lindell & Whitney, 2001). Restaurant preference captured the preference for a restaurant in terms of friendly service personnel, healthy meals, and sanitary conditions and was measured by three items adapted from Gupta, McLaughlin, and Gomez (2007). This variable was a suitable MV because it measured the individual preference and was unrelated to all latent variables in this study (i.e., data analytics capability, bricolage, innovation orientation, and servitization). The lowest positive correlation between restaurant preference and other latent variables (*r* = 0.019) was used to adjust variable correlations (Lindell & Whitney, 2001). The results in Table II illustrate that the correlations remained significant after adjustment, suggesting that common method bias was not a serious concern in this study.

Appendix C.

Results of Post-hoc Analyses

Table C I. Results of post-hoc analysis 1

	Model1	Model2	Model3	Model4
	Product-oriented services	Customer-oriented services	Product-oriented services	Customer-oriented services
Data analytics capability(DAC)	0.275***	0.180***	0.129	0.067
	(0.060)	(0.036)	(0.369)	(0.220)
Innovation orientation	0.157	0.207***	0.040	0.116
	(0.101)	(0.060)	(0.310)	(0.185)
DAC×Innovation orientation			0.034	0.027
			(0.086)	(0.051)
Marketing capability	0.360***	0.496***	0.356***	0.493***
	(0.100)	(0.060)	(0.101)	(0.060)
Firm size	−0.085	−0.049	−0.086	−0.049
	(0.060)	(0.036)	(0.060)	(0.036)
Firm age	0.017	0.026	0.022	0.030
	(0.147)	(0.088)	(0.148)	(0.088)
Consumer products [a]	−0.479*	−0.173	−0.471*	−0.167
	(0.201)	(0.120)	(0.202)	(0.121)
Petroleum and chemical [a]	−1.148***	−0.335**	−1.143***	−0.331**
	(0.176)	(0.105)	(0.177)	(0.105)
Machinery [a]	−1.054***	−0.193	−1.048***	−0.188
	(0.176)	(0.105)	(0.177)	(0.106)
Electronics [a]	0.175	0.114	0.179	0.117
	(0.162)	(0.097)	(0.163)	(0.097)
Constant	2.012**	1.607***	2.506	1.989*
	(0.664)	(0.397)	(1.400)	(0.836)
Degree of freedom	9.000	9.000	10.000	10.000
RMSE	1.122	0.670	1.123	0.670
R^2	0.261	0.306	0.262	0.306

* $p < 0.05$, ** $p < 0.01$, *** $p<0.001$. [a] Dummy variable. Standard errors in parentheses.

Table C II. Results of post-hoc analysis 2

	Model1	Model2	Model3	Model4
	Product-oriented services	Customer-oriented services	Product-oriented services	Customer-oriented services
Bricolage	0.321*	0.220*	−0.569	−0.300
	(0.162)	(0.097)	(0.439)	(0.263)
Innovation orientation	0.042	0.126	−0.831	−0.384
	(0.144)	(0.087)	(0.426)	(0.255)
Bricolage × Innovation orientation			0.216*	0.126*
			(0.099)	(0.059)
Marketing capability	0.402***	0.522***	0.392***	0.516***
	(0.102)	(0.061)	(0.102)	(0.061)
Firm size	−0.058	−0.031	−0.062	−0.033
	(0.061)	(0.037)	(0.061)	(0.036)
Firm age	−0.090	−0.044	−0.074	−0.035
	(0.149)	(0.089)	(0.148)	(0.089)
Consumer products [a]	−0.411*	−0.128	−0.435*	−0.142
	(0.206)	(0.124)	(0.206)	(0.123)
Petroleum and chemical [a]	−1.094***	−0.299**	−1.087***	−0.294**
	(0.181)	(0.108)	(0.180)	(0.108)
Machinery [a]	−0.972***	−0.138	−0.961***	−0.131
	(0.180)	(0.108)	(0.179)	(0.108)
Electronics [a]	0.187	0.122	0.186	0.121
	(0.166)	(0.099)	(0.165)	(0.099)
Constant	2.004**	1.593***	5.564**	3.670***
	(0.694)	(0.416)	(1.773)	(1.063)
Degree of freedom	9.000	9.000	10.000	10.000
RMSE	1.146	0.687	1.141	0.684
R^2	0.229	0.270	0.238	0.278

* $p < 0.05$, ** $p < 0.01$, *** $p<0.001$. [a] Dummy variable. Standard errors in parentheses.

Table C III. Results of post-hoc analysis 3

	Model1		Model2	
	Product-oriented services		Customer-oriented services	
Regression results	Coefficients	SE	Coefficients	SE
Data analytics capability (DAC)	0.249***	0.061	0.164***	0.036
Bricolage	0.270	0.160	−0.123	0.260
Innovation orientation	0.033	0.143	−0.188	0.253
Bricolage×Innovation orientation	0.134	0.099	0.072	0.059
Marketing capability	0.334***	0.101	0.478***	0.060
Firm size	−0.093	0.060	−0.054	0.036
Firm age	0.016	0.147	0.025	0.088
Consumer products [a]	−0.464*	0.202	−0.161	0.120
Petroleum and chemical [a]	−1.115***	0.176	−0.313**	0.105
Machinery [a]	−1.018***	0.177	−0.169	0.105
Electronics [a]	0.169	0.162	0.110	0.097
R^2	0.269		0.314	
F value	13.059		16.230	
Conditional indirect effect (bootstrapping analysis)				
	Moderator (Innovation orientation)	Indirect effect	Boot SE	95% Boot CI
DAC→Bricolage→Product-oriented services	Low (−1 SD)	0.021	0.021	[−0.022, 0.064]
	High (+1 SD)	0.039	0.025	[0.002, 0.010]
	Difference	0.017	0.021	[−0.002, 0.080]
DAC→Bricolage→Customer-oriented services	Low (−1 SD)	0.016	0.014	[−0.007, 0.047]
	High (+1 SD)	0.025	0.015	[0.001, 0.059]
	Difference	0.009	0.010	[−0.010, 0.032]
Index of moderated mediation bootstrapping analysis				
		Index	Boot SE	95% Boot CI
Moderated mediation for product-oriented services		0.015	0.018	[−0.002, 0.068]
Moderated mediation for customer-oriented services		0.008	0.008	[−0.009, 0.027]

* $p < 0.05$, ** $p < 0.01$, *** $p<0.001$. [a] Dummy variable. SE = standard error; CI = confidence interval.