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SPECIAL ISSUE

Data-Driven Product Development Transformation: A Case Study from the Perspective of Adaptive Change in Organizational Routines

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Abstract

Extant research mostly focuses on the impact of big data on product development (PD) process and performance, and yet there is a lack of theoretical exploration of the transformation path, realization mechanism and transformation paradigm while moving from experience-based PD (EBPD) to data-driven PD (DDPD). This paper, from the integrated perspective of adaptive change and organizational routines, and based on an in-depth case study of HSTYLE, proposes a two-stage transformation model for moving from EBPD to DDPD, dissects the adaptive change mechanism of organizational routines for DDPD, puts forward a theoretical model for the transformation paradigm for DDPD, and provides an innovative interpretation of the connotation of data-driven. This paper constructs a theory for DDPD transformation that comprises three aspects: transformation path, realization mechanism and transformation paradigm. Conclusions of this paper have policy implications for enterprises in their practice on data-driven product innovation in the digital economy era.

Keywords product development transformation, data driven, organizational routine change, adaptive change, case study

1 Introduction

As enterprises like ZARA, H&M, Uniqlo, Procter & Gamble, etc. have ventured into product development innovation (PDI)[1] leveraging big data one after another, big data analytics not only boosts the PDI model, but also improves the quality of PDI decision-making to build a firm's dynamic capabilities (Johnson et al., 2017; Pisano et al., 2015). However, "Cherries are delicious but laborious to plant" as the saying goes. Numerous are the difficulties that enterprises encounter when they engage in data-driven PD (DDPD), especially in the face of competing concerns (Svahn et al., 2017). On the one hand, when a firm is top-down in making DDPD decisions, there may be strong resistance at the organizational level, resulting in failure of the transformation; on the other hand, when a firm adopts the incremental adjustment approach to induce product departments to carry out DDPD, it may be bogged down by the inertia of experience-based product development (EBPD), hobbling its DDPD efforts (Sebastian et al., 2017). A 2016 Gartner report *Survey*

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[1] PD innovation is a very broad concept, and there are significant differences in PD innovation of different products, ranging from pharmaceuticals, biotechnology, nanotechnology and other R&D activities, etc. to innovations in the processes and appearances of fast–moving consumer goods. This article mainly focuses on the development and innovation of new products in the fast–moving consumer goods market, and does not involve the R&D of high–tech products.

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Analysis:Big Data Investments Begin Tapering in 2016 indicates that 85% of data-driven organizational transformation fails; Accenture's *China Digital Transformation Index 2018* reports that only 7% of Chinese enterprises have successfully achieved DDPD. Therefore, transformation from EBPD to DDPD is not only a key area in the digital transformation of enterprises, but also a hot topic in organizational management theories in the digital economy era, and a thorny issue in business practice as well.

In essence, transformation to DDPD is a process of organizational routines enabled by big data analytics. How an enterprise achieves data-driven transformation in its organizational routines has been a long-standing area of academic focus (Besson & Rowe, 2012). Different from former changes in organizational routines, big data-driven management decisions are "unconscious" decisions which will entail complex trust issues in the process of organizational transformation (OT). To solve these issues, a combination of radical top-down change on the part of the executive team and incremental bottom-up cross-department alignment is required (Burgelman et al., 2018). Meanwhile, routine changes in a data-driven OT require balancing between human decision-making and data-driven decision-making, highlighting the complexity of human-machine collaboration in the transformation, and underscoring the iterative nature of adaptation in the transformation (Yeow et al., 2018). Therefore, DDPD transformation is not only a question of changing organizational routines, which are the object of OT, but also a question of organizational adaptability, which is the mode of OT. Only when both the object and the mode of OT are treated as a whole can there be more insightful dissection of how EBPD transforms into DDPD. Exploration into the organizational routine adaptability, which is an integration of organizational routine change and organizational adaptability, will yield better insights into the characteristics of the transformation from EBPD to DDPD, will better meet the complex needs of the transformation, and will deepen research into DDPD and OT.

With the rapid diffusion of big data and artificial intelligence (AI) technologies, the DDPD transformation paradigm has become a major trend in enterprise innovation in the digital economy era. Extant research in the field of big data describes "data-driven" as a data-enabled management decision-making mode (Woerner & Wixom, 2015), lacking specific analysis of the connotation of "data-driven," and lacking in-depth discussion on the transformation paradigm of DDPD. DDPD requires not only the collection of multi-dimensional internal and external data, building a corresponding big data platform and improving the level of big data analytics, but also adaptive changes to organizational routines to promote the transformation of enterprises to the DDPD mode. Clearly, a deeper understanding of big data, of DDPD and of OT is also a frontier topic in the intersection of the three areas that a theoretical exploration is urgently needed. As advocated by Chanias et al. (2019), further studies need to discuss questions relating the problem of the implementation of data-driven organizational change process.

Accordingly, this paper attempts to, from the perspective of adaptive change of organizational routines, by using the exploratory single-case study method, conduct a longitudinal case study on HSTYLE to explore the theory of DDPD transformation. We aim to specifically answer the following three questions. First, what path can an enterprise take to transform from EBPD to DDPD? Second, in the process of DDPD transformation, how can enterprises achieve the transformation successfully through different adaptive organizational routine changes? Third, what are the main characteristics of the DDPD transformation paradigm? In short, the above three questions are about the transformation

path, the realization mechanism and the transformation paradigm of DDPD.

The present studies have left theoretical gaps of varying degrees. To address these gaps as embodied in the above three questions, the following parts of the paper are arranged: Part 2 is literature review, Part 3 is research methodology, Part 4 is research findings, Part 5 is discussion, and Part 6 is theoretical contributions, research limitations and future prospects.

2 Literature Review

2.1 EBPD vs DDPD

2.1.1 EBPD

In a traditional context, enterprises improve PD performance by collecting and processing small-sample data sets. However, because of the cost of traditional data collection, the data quality and data analysis capabilities are hard to ensure. Therefore, the data analysis results are only used as a necessary complement to the PD decisions mostly based on organizational and even individual experience (Hoyer et al., 2010). Specifically, enterprises use the technical expertise of internal employees to achieve self-dependent innovation on the one hand; they integrate PD expertise of external entities through joint ventures and strategic alliances, mergers and acquisitions, crowd-sourcing, etc. to realize open innovation on the other hand (Lü et al., 2017). Be it external cooperation or internal innovation, extant research on PD management emphasizes leveraging the expertise of partners or internal staff to improve the innovation performance of PD. However, scholars are also aware that the EBPD model is problem-ridden: high costs, long cycles and high risks; and that the situation can be improved and innovated through big data analytics (Pisano et al., 2015).

2.1.2 DDPD

The term big data is often used to describe large-scale, complex and real-time data flows, usually defined as three information assets: big volume, high speed (velocity) and big variety (Gupta & George, 2016). Regarding PD, first of all, big data changes the mode of enterprise PD. Businesses, armed with the methods and tools provided by big data analytics, can build detailed consumer behavior profiles, helping them gain valuable insights, and even automatically making highly sophisticated PD decisions which can replace human PD expertise (Brynjolfsson & McAfee, 2011). Second, big data reduces the cost of PD, shortens the PD cycle, and helps control PD risks. For example, big data improves customers' willingness for product adoption and reduces costs. This can help companies reduce new PD cycle by 3 to 5 years, etc. (Tan & Zhan, 2017). Finally, big data makes it possible for ordinary consumers to participate in the PD process in a data-based manner, making consumer participation no longer an "exclusive privilege" for the lead users. In the three key links of planning, design and testing of PD, big data not only provides low-cost and high-efficiency means and tools for enterprises to collect consumer data, but also provides consumers with key paths to participate in PD, and with means for them to express their willingness to pay (Xiao et al., 2018). For example, businesses can track consumer clicks on new products on internet platforms and analyze their behavior which will support the enterprises' efforts in secondary PD (Johnson et al., 2017).

In short, extant research on PD management has focused on the operation mode of the DDPD process, and has also paid attention to the mechanism of big data's impact

on PD performance, but there is little in-depth research on how EBPD transforms to DDPD.

2.2 Organizational Routine Change and Organizational Adaptive Change

2.2.1 Organizational Routine Change

Organizational routines refer to interdependent, repetitive, and identifiable rules of action and patterns of behavior that are jointly implemented by multiple actors (Bresman, 2013), such as when enterprises gather product ideas, or implement the PD processes, etc. Early research views organizational routines as an inseparable unit, and routines as entities; that organizational routines adapt to changes in the external environment through evolutionary cycles of variation and selection (Nelson & Winter, 1982). However, research from the entity perspective does not clarify the process mechanisms of how new routines replace old ones (Greve, 2008). To address this limitation, Feldman and Pentland (2003) regard organizational routines as a renewable system, proposing that organizational routines consist of Performative part (P) and Ostensive part (O). The two parts are interdependent and they interplay to make organizational routines both stable and dynamic. In this way, while inheriting and developing Nelson and Winter's (1982) point of view, they have highlighted the active roles of the actors when performing organizational routines, and have thus overcome the limitations of the routine-entity view which cannot explain the self-evolution of routines.

The renewable system view of organizational routines holds that the O of organizational routines is the idealized forms of routines, referring to the implicit knowledge contained in organizational routines, specific rules and specific examples, etc.; the P is the process from organizational routine's O to actions, or actual performances of the routines by specific people, at specific times, in specific places (Pentland et al., 2012). The P can create and reconstruct the O; conversely, the O can guide, constrain and enable the P (Berente et al., 2016). In addition to the O and P parts, a third part or the Material part (M) is also regarded as one of the important components of organizational routines (Volkoff et al., 2007). The M refers to the functions and characteristics of technical artifacts, including information technology infrastructure, software systems and the interactions between humans and technology, etc. (Pentland et al., 2012). Extant research indicates that M is an important theoretical perspective into information technology's part in organizational change and transformation. Especially in the implementation of information systems, the M needs to be mutually consistent with the O and P in order to achieve organizational change and transformation (Faraj & Azad, 2012).

Therefore, from the perspective of a renewable system of organizational routines, organizational routine change is essentially the adaptation process of the O, P, and M. In the process of interaction among the three, there is a close connection between organizational routine change and business model transformation (Rerup & Feldman, 2011).

2.2.2 Organizational Adaptive Change

From the perspective of evolutionary biology, adaptation means that individuals or systems can better adapt to changes by improving their genetic or behavioral characteristics and

retain those adaptive characteristics (Futuyama,1979). Adaptation, from a complexity perspective refers to the ways in which social groups deal with issues that are closely related to them in a more sophisticated approach (O′Brien & Holland, 1992). Organizational adaptive change can be studied from sociology, biology, management and complexity science. It is believed that strategic transformation and organizational adaptation are two key factors in building an environment-adaptive organization (Holland, 1998). Therefore, organizational adaptation can be the dynamic equilibrium between an organization and the situation it is in (Xu et al., 2017), or it can be the organizational capability to respond to environmental changes. Different internal and external environments and different organizational properties require organizations to cultivate different organizational adaptability (Lü et al., 2007).

Adaptive management refers to making management decisions and plans based on existing knowledge of the system and previous practices, and then strictly implementing them according to the plans. It is often summarized as "learning by doing" or learning by managing (Williams, 2011). Adaptive management includes active and passive adaptive mechanisms. Among them, active adaptation refers to the problem-solving mechanism by which enterprises, while adopting multiple management strategies at the same time, simulate, execute, monitor and finally evaluate those management strategies to achieve optimum management performance; passive adaptation refers to the problem-solving mechanism by which an enterprise, taking a single management decision, employs adaptive learning procedures to simulate, execute, monitor, and evaluate that single decision (Walters & Holling, 1990). Therefore, organizational adaptive change can be understood as an organization's effort to innovate or adjust and optimize its existing organizational adaptive management to better adapt to its external environment and internal resources (Kauffman, 1993).

2.2.3 An Integrated Perspective on Adaptive Change in Organizational Routines

On the one hand, current research on organizational routine change believes that when actors execute organizational routines, they will compare the O with the implementation results and revise or adjust the O (Cyert & March, 1963). However, multiple organizational routine changes often happen at the same time in an organization (Sele & Grand, 2016) and yet most extant research analyzes a single routine change as an analysis unit to examine the process of organizational routine change, lacking in-depth analysis of the simultaneous adaptive changes an organization undergoes according to the different attributes of organizational routines (Deken et al., 2016). The embedding of big data technology will entail multiple simultaneous changes in PD routines, so it is difficult to use the extant organizational practice change theory as a reference for in-depth analysis of the DDPD transformation process.

On the other hand, extant research on organizational adaptive change emphasizes the complexity evolution of the system, and believes that different change units within the system communicate with the external environment to formulate rational response strategies (Parmigiani & Howard-Grenville, 2011). Therefore, theories on organizational adaptive change can be combined with the theory of organizational routine change, so as to make up for the limitations of the extant research on organizational routine change which has difficulty explaining the adaptive change of multiple routines. The condition for

integrating the theory of organizational routine change with the theory of organizational adaptation lies in the fact that the two delineate the organizational change process from different perspectives. Generally, organizational routine is the object of organizational change, reflecting and embodying the connotation of change (Salvato & Rerup, 2018) while organizational adaptation reflects and embodies the pattern or outcome of change (Girod & Whittington, 2015).

Furthermore, the application of big data mainly affects the adaptations of corporate organizational routines (Woerner & Wixom, 2015). Research based on the perspective of organizational routine change can deepen understanding of the connotation of the organizational change process in DDPD transformation. Meanwhile, the process of embedding big data into existing organizational routines will entail complex decision-making trust issues (Salovaara et al., 2019), requiring organizational adaptive innovation to balance the relationship between data-driven decision-making and human decision-making (Yeow et al., 2018). Analysis based on the perspective of organizational adaptive change can more accurately delineate the realization mechanism of PD transformation. Therefore, an integrated perspective on the adaptive change of organizational routines can provide a suitable theoretical perspective for DDPD transformation.

To sum up, on the one hand, current research has done much work on the impact of big data on the processes and performance of PD, and on the conceptual models of PD based on big data (Cui & Wu, 2016). On the other hand, continuous research on the transition between different PD paradigms (Luo et al., 2014), such as from closed innovation to open innovation, from incremental innovation to radical innovation, and from continuous innovation to disruptive innovation (Chesbrough, 2003; Christensen, 1997; Foss et al., 2013). However, current research lacks in-depth empirical studies on the transformation from EBPD to DDPD. And there has been no discussion on the transformation of one PD mode into the other from the perspective of adaptive change of organizational routines. Accordingly, this paper focuses on the transformation from EBPD to DDPD: its path, realization mechanism and transformation paradigm.

3 Research Methodology

3.1 Methodology and Sample Selection

This paper focuses on how enterprises can achieve DDPD transformation through adaptive change in organizational routines. The exploratory single-case study approach method is suitable for answering such questions for the following reasons: First, this paper aims to explore the transformation of enterprises from EBPD to DDPD, including the transformation path, realization mechanism, and transformation paradigm, which lends itself well to the case study method (Yin, 2013); second, for most traditional enterprises which are not born-digital,[2] few have been successful in their DDPD transformation (Abbasi et al., 2016). This is a new phenomenon in management practice and raises new questions. Using the exploratory single-case study method to discover new ideas and identify new patterns

[2] Pre-digital organizations refer to organizations whose products, services, business models, and competitive environments belong to traditional industries, such as Midea, Procter & Gamble, etc. that are engaged in traditional manufacturing (Chanias et al., 2019). In contrast to such pre-digital organizations are born-digital organizations, which are based on digital technology from the start in their products, services, and business models, such as Tencent, Baidu, and Alibaba. Born-digital organizations are built on the basis of big data technology, and there is no DDPD transformation (Bharadwaj et al., 2013). This paper mainly focuses on the DDPD transformation process of pre-digital organizations.

can better answer those questions (Eisenhardt & Graebner, 2007); third, organizational routine change and organizational adaptation are constructs with contextual characteristics, which need to be deeply analyzed in specific contexts. The single-case research approach is an appropriate research method for exploring contextualized issues (Salvato & Rerup, 2011). An in-depth study of a single-case enterprise can reveal the dynamics between the O, P and M of different organizational routines and the characteristics of organizational adaptation (Pentland & Feldman, 2008).

In terms of sample selection, this paper selects a Chinese internet apparel brand HSTYLE as the object of our exploratory single case study. The core reasons for this selection are as follows. First, the Chinese internet apparel industry in which HSTYLE operates is facing fierce industry competition, so much so that both internet platforms and apparel brand businesses believe that transformation to DDPD is an inevitable choice to build new competitive edges. Second, starting from 2012, HSTYLE has been focusing on big data-refined management of PD as its primary development direction. After seven years of continuous changes, a DDPD model has been established. In 2018, HSTYLE even launched the Sophon AI fashion trend prediction project, which can predict apparel styles and popular colors based on big data. Third, supported by the DDPD model, HSTYLE has won the Tmall "Double Eleven" internet apparel brand champion for six consecutive years from 2014 to 2019, and its product sold out rate is as high as more than 95%, rocketing HSTYLE's PD innovation performance to the leading level in the industry. Therefore, based on the research questions in this paper, the HSTYLE case is extreme and enlightening and is a suitable subject for this study. In addition, there has been no previous study of HSTYLE's case that analyzes PD transformation from the perspective of adaptive change in organizational routines.

3.2 Enterprise Case Research and Data Collection

3.2.1 Enterprise Case Research

Preparation of the interview outline and the conducting of interviews. The interview outline for this study focuses on the transformation process to DDPD, or how different PD routines transform through adaptive changes. Therefore, we design the interview questions with an eye on the business founders, executive teams, heads of the core departments and the middle and grassroots employees of all departments. During the research process, we refine and add new questions to the interview outline when the questions are found to be not dovetailing with the situation in HSTYLE. At the same time, when questions not covered by the interviews are found in the subsequent paper writing up stage, we fill up the gaps in our research through adding supplementary interviews and multiple rounds of iterations to ensure the integrity and authenticity of the data.

The research team's work on HSTYLE begins in November 2016, with the intensive periods being July to August 2017 and January 2019; other periods are supplementary interviews for aspects uncovered during the intensive periods. A total of 42 interviews are conducted, with a duration of 40.5 recorded hours and 487,000 words of transcribed texts (see Table 1). Before the interviews, the team collects and sorts out relevant data according to the interview themes, and then works out interview questions with focuses. Semi-structured interviews are used, with four to five researchers participating in each interview session. In order to make the interview data as objective and as truthful as possible,

each interview is done on only one interviewee, and the recording has been kept strictly confidential.

Table 1 Description of the Interviews with HSTYLE

Interview time	Interview subjects and their positions	Duration (in Hours)	Transcript words (in 10,000)
1st time 2016/11/26	Group vice president	3	4.1
2nd time 2017/7/24	Group vice president (2), manager of operation department, director of information department, manager of production department, director of planning department, director of production department	6	7.8
3rd time 2017/8/28–2017/8/29	Group vice president, manager (2) of information dept, manager of planning department, manager (2) of production department, customer service department manager (2), marketing department manager (3), product department manager (3), general manager office staff (3)	12	14.5
4th time 2018/5/16	Head of strategic cooperation department, director of information department	2.5	3.3
5th time 2019/1/1–2019/1/30	Manager of information department, product manager (2), planning manager (2), production director, marketing manager (2), planning director, brand manager (2)	15	16
6th time 2019/5/19	Group founder, product director, product manager, production department manager	2	3
Total	42 people	40.5	48.7

Note: The numbers in parenthesis indicate number of interviewees, with the number 1 as the default and omitted.

Field observation. In addition to the interviews, after two months of preparation, the research team has two members conduct field observation for one month in HSTYLE from January 1 to January 30, 2019. The main process is as follows. First, researchers are stationed in the case enterprise, select executives responsible for big data and PD and start field observations on them. On the condition of not affecting the executives' work, researchers observe and record their daily work, including their discussions with enterprise founders, board members, etc. on PD-related matters, consultations with heads of various departments, and the day-to-day communications with employees. Second, the researchers conduct field observations on the middle and grassroots management, who are also stakeholders in the DDPD transformation in the case enterprise.

Finally, we integrate the field observation data with those garnered from the interviews by cross examining, or corroborating. Field observations not only enrich the data of this case study, but also deepen the researchers' cognition and understanding of the DDPD transformation of the case enterprise.

3.2.2 Data Collection

This study collected data from four aspects to improve the reliability and validity of the case (Yin, 2013).

Semi-structured interviews. These form one of the core sources of data collection. During the interviews, the research team tries to focus on new issues, new perspectives, new ideas and new concepts that are not present in current theories. And to avoid being overly structured, we constantly revise the interview outline after reviewing the interviewees' answers to the questions. In addition, this paper focuses on examining the internal dynamics of organizational routines, which reflect the conflicts in organizational change and the resolution strategies for those conflicts.

Field observation journal. This constitutes another core data source for the study. By observing, recording and analyzing the day-to-day activities of HSTYLE's PD executives, heads of stakeholder departments, middle and grassroots managers, their meeting minutes and communication processes, researchers make a journal of 100,000 words, which brings the discoveries of the case study closer to reality.

Case enterprise's corporate archives. Archives include HSTYLE's internal organigram, operations flow charts, employee training manuals, internal publications, external publicity materials, etc. In addition, through an in-depth understanding of the enterprise resource planning (ERP) system, routine changes and policy provisions, the research team explores and analyzes the process and the states before, during and after the change.

Second-hand material. HSTYLE is a well-known brand in the internet market with an abundance of books, databases of journals, newspapers and online articles on its PD model. In particular, the numerous reports about HSTYLE founder's emphasis on the application of big data on various occasions provide objective confirmation for the writing up of this case.

3.3 Data Coding and Analysis

This paper strictly follows the analysis recommendations for case studies using qualitative data, and divides the coding analysis process into three stages: data reduction, data display, conclusions drawing and verification (Eisenhardt, 1989; Miles & Huberman, 1994). There is an interdependent relationship between the above three stages. The data reduction stage is mainly to select and simplify the existing qualitative textual data, build the corresponding coding table to codify the data. The data display stage mainly focuses on comparison and analysis of the reduced data in the coding table. The conclusion drawing and verification stage is to derive a corresponding theoretical framework from continuous iteration and cross verification.

Data reduction. First, the research team classifies the qualitative data of HSTYLE, and marks the recorded data as HD1–HD15; second-hand data are labeled HD16. Due to the large volume of HSTYLE's recordings, the research team uses a back-to-back encoding

process to encode them independently. The team is divided into two groups, each consisting of three to five people. Before the coding work, the two groups jointly hammer out the coding scheme, including specific constructs, key processes, and the core logic between the constructs. In the process of coding, core constructs are identified according to the coding scheme. Some constructs come from the literature, such as organizational routines, the O, the P, and the M etc.; some come from the research framework, such as DDPD transformation, etc.

Data display. On the basis of data reduction, the research team conducts a comparative analysis of the coded materials. To ensure the accuracy of the coding results, the team conducts in-group discussions and inter-group discussions over inconsistent coding results until a consensus is reached. When a dispute arises over certain coding, a third-party is sought to provide opinions and suggestions so as to maintain the consistency of the coding as much as possible.

Conclusion and verification. On the basis of the data display, the research team constructs a theoretical framework based on extant literature. For example, this research focuses on how an enterprise achieves DDPD transformation through adaptive change of organizational routines, and we derive EBPD, DDPD, organizational routine adaptive change, etc. According to the case study strategy, we undertake multiple iterations of "data → relationship → framework" at this stage. Through corroboration between different data sources, the explanatory power of the theoretical framework on the phenomena is reinforced (Stake, 2005).

4 Research Findings

4.1 EBPD before Transformation

In light of current research's classification of corporate PD practices (Zhan et al., 2018), HSTYLE's PD can be divided into product planning routines, product design routines, and product testing routines. The specific steps involved in each of the organizational routines are shown in Table 2. Before the PD transformation, three organizational routines feature EBPD management decision-making in the product department and other departments.

Table 2 Specific Steps of Core Organizational Routines in PD

Core organizational routines	Specific steps
Product planning routines	(1) Information research, (2) design planning, (3) value planning, (4) money planning, (5) planning confirmation
Product design routines	(1) PD plan, (2) product reserve, (3) product preliminary review, (4) product general review, (5) prototype production
Product testing routines	(1) Place initial order, (2) stock initial order, (3) analyze the initial order, (4) place reorder, (5) stock reorder

Next, we use the product testing routines shown in Figure 1 as an example to illustrate this point in detail. Five core steps in product testing routines are performed by the Product Department, Marketing Department and Production Department (PMP departments) based on PD experience. First, the Product Department puts forward the initial production order; upon receiving the order, the Production Department dispatches the order to suppliers for

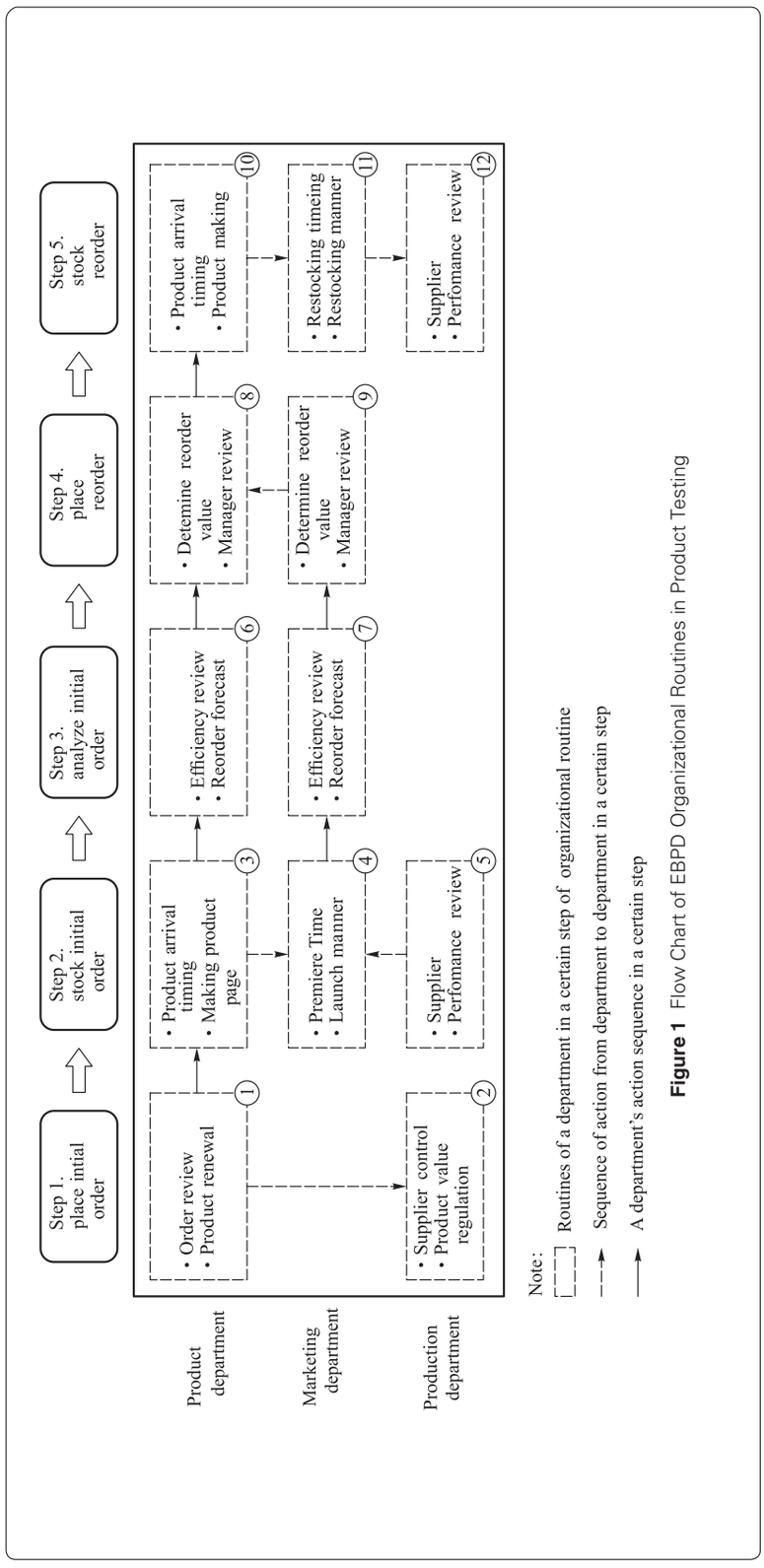

Figure 1 Flow Chart of EBPD Organizational Routines in Product Testing

production (process ① and ② in Figure 1). Second, the Product Department makes the product details page, and the Marketing Department launches the new product according to requirements of platform events; the Production Department completes production of the initial order (processes ③ to ⑤ in Figure 1). Third, in view of the actual sales figures of the initial product, the Product Department and the Marketing Department classify the product into hot-sale, best-sale, slaw-sale, normal-sale (HBSN) categories according to experience (processes ⑥ and ⑦ in Figure 1). Fourth, the Product and Marketing departments allocate production resources and marketing resources for the product and place reorders according to the new product's verified actual sales (processes ⑧ and ⑨ in Figure 1). Fifth, the PMP departments restock the reorders (processes ⑩ to ⑫ in Figure 1).

There are three main problems with experience-based (EB) product testing routines, namely, high dependence on the competence of the testing agents, limited rationality in the testing results, and high cost of testing collaboration. First, it is highly dependent on the competence of the testing agents. The PMP departments formulate new product testing plans mainly on the basis of each department's PD experience. Although the Product Department will also reference the sales figures of the initial order, professional analyses provided by e-commerce platforms and external consulting firms, those are mainly used to confirm their own experience and ideas. Second, the testing results are rife with limited rationality and irrationality. In HSTYLE the decision on product testing is delegated to the PMP departments. The PD decisions of different departments may be based on their own departmental interests, resulting in short-term behavior at the expense of the whole corporate interests. Finally, the cost of testing collaboration is high. There are different interests among the PMP departments. In a non-big data context, there are differences in the formulation of testing results among the different departments. In the end, only relatively consistent results can be achieved through long collective consultations and competitions. Similarly, EB product planning routines and product design routines are rife with the same issues and challenges. With the increasingly fierce competition in the internet market, HSTYLE executive team realized the necessity and urgency of PD transformation.

4.2 Transformation from EBPD to DDPD

This case study reveals that the transformation process of HSTYLE's PD is essentially the dynamics between the M, O and P. The interactions among the three parts mainly goes through two stages—data-entailed conflicts identification and resolution stage (2012–2015), and the acceptance and enhancement stage of the rule of data (ROD) (2016–2019).

4.2.1 Data-Entailed Conflicts Identification and Resolution Stage (2012–2015)

In the process of embedding big data into product planning routines, product design routines and product testing routines, it is first necessary to reconstruct the original O of the PD routines; with the new O embedded in place, a new M appears, and the mutual adaptation between new O and new M entails changes to P, and hence new P appears. However, conflicts often arise between new O, new M and new P, and enterprises need to identify such conflicts and work out adaptive resolution strategies.

Data embedded in product planning: Technical conflicts identification and passive

adaptation. In 2012, while exchanging ideas with Tmall, Vipshop, JD.com and other players in the industry, HSTYLE executives realized that big-data-driven product planning would be the core competitive advantage in future development of the internet market. As deputy general manager of HSTYLE mentioned: "By analyzing multiple dimensions of big data, we can predict what consumers really like, which is actually a testing of societal needs." To this end, HSTYLE hired an external consulting company to understand how to build data-driven product planning, hoping to manage the full life cycle of PD through big data and to construct the new O of data-driven product planning routines. With constructing a new O as the objective, HSTYLE decided to let the Planning Department take the initiative to build a big data system as the M of data-driven planning.

On the one hand, as even the basic data of a product was not available at all, the Planning Department went to the warehouse to carry out a product inventory to understand past product planning and historical data. On the other hand, the Planning Department keenly studied the product planning and operation rhythms of the top-ranking players on internet platforms to learn from competitor products. Finally, on the basis of internal operations data and of the planning and operations data of competitor products, as well as the product planning logic inherent in big data, the Planning Department proposed the very first data-driven product planning scheme.

However, a conflict between data-driven product planning and specific business unit routines arose. Specifically, although the PMP departments were also aware of the importance of data in formulating product planning, and admitted that big data could improve the level of precision in product planning, they were dubious that data analysis capabilities and results produced by the Planning Department could truly reflect market demands. A typical case in point occurred in the Fall of 2013, when the Planning Department produced a relatively safe plan, which the Product Department and Production Department refused to implement. As the director of Production Department mentioned: "We judge from experience that the market at that time is in short supply, and yet the big data plan does not conform to the objective situation of the internet market." During the planning process with data embedded, the data analysis technology and analysis capabilities of the Planning Department could not meet the business needs and objectives by the business departments, resulting in conflicts.

In the face of technical conflicts arising from data embedded product planning, HSTYLE adopted a passive adaptation mechanism to deal with it. Case data indicated that HSTYLE's passive adaptation referred to a problem-solving mechanism of resorting to a single adaptation strategy to the M of big data in the product planning routines to improve data analysis performance by enforcing the single strategy. To be specific, the senior management team of HSTYLE made it compulsory to execute the product plan formulated by the Planning Department based on big data, and empowered the Planning Department to review the orders placed by the Product Department. If the PMP departments did not implement the product plan based on big data, all relevant parties would be punished. A typical example was that in 2013, after the Product Department refused to implement a big data-backed plan, all the responsible managers and supervisors of the PMP departments were each fined 1,000 yuan.

The core reason why HSTYLE adopted a passive adaptation mechanism for technical conflicts was that the level of resistance to big data in various departments of the organization was relatively low. On the one hand, the business departments were aware

that there must be technical problems in the data system, but on the other hand, they were also aware that old EB product planning would incur huge risks and uncertainties to the enterprise, and so they were willing to enforce the use of the new system even when there was resistance among members of the departments.

Data embedded in product design: Value conflicts and alignments. In 2013, HSTYLE restructured its product design routines, making them data-driven. The Information Center manager described the O of the corporate routines like this, "We want to build a set of data tools with which we would like to, under the premise of their acceptance, influence the PD activity of the buyers such as letting them know consumers' favorite patterns, materials, and prints, etc." Under the guidance of the O, HSTYLE builts the M of a big data system to assist product design. Specifically, HSTYLE obtained competitor business data, consumer search data and review data from large internet platforms and used data analytics to profile consumer preferences. However, buyers and designers in the Product Department generally believed that clothing as a non-standard product was difficult to be predicted on the basis of rational data, algorithms and models, which were useful for the designing process, and that it still needed to rely on the sensible judgement of the buyers and designers, and therefore rejected the use of data system-aided designing. The misalignment between the inherent management logic of big data-aided design and the value criteria on the part of the designers negatively affected the adoption of the data system. HSTYLE identified the conflict as value conflict.

Faced with the value conflict arising from data embedding in product design, HSTYLE adopted the mutual alignment strategy to align the data system with the new product design routines to deal with it. Data from the case showed that the mutual alignment strategy in HSTYLE referred to aligning the M of big data system with the O of the design routines through mutual adaptation as a problem-solving mechanism. Specifically, HSTYLE's senior management team did not insist on executing outcomes from the data analysis in the product design process, but required that buyers in the Product Department shall assist the Planning Department and the Information Center to adjust the data system, with the ultimate goal of achieving alignment between new product design routines and the data system. On the one hand, HSTYLE set up data analysis specialists for the Product Department to help the product teams better understand the results and the process of the data analysis; and the buyers reported design needs to the analysis specialists in order to improve the data system functions. On the other hand, HSTYLE set up a data analysis team in the Planning Department and had the team discuss key issues with the Product Department in the PD design process to bring data analysis closer to the design requirements.

The core reason why HSTYLE adopted mutual alignment strategy for the value conflict was that, compared with technical conflicts, the value conflict generated a higher level of resistance in the Product Department. The level of resistance was relatively high in the Product Department not only because of the learning cost incurred in the work, but also, more importantly, because of the Product Department's perception that there was a substitution relationship between the data system and the buyers' work. Therefore, the executive team of HSTYLE had to use the mutual alignment strategy to communicate the value of the data system to the buyers and designers, and to help them gradually realize that the data system and the buyers' work are essentially complementary and mutually beneficial.

Data embedded in product testing: Power conflict and active adaptation. In response to the changes in product testing routines, HSTYLE hoped to find the most profitable new products through big data testing and in turn focus on the production and sales of such products. That was the attempted O of data-driven product testing routines. This new O placed a higher requirement for the data system. In 2013, HSTYLE decided to build its own information systems, starting from the basic warehouse management system, order management system, and gradually building up a data system with the necessary hardware and software to support new product testing. At the same time, HSTYLE started analyzing historical data of consumers' purchase behavior on e-commerce platforms, including hot-selling consumer categories and popular products in the current season. On the basis of in-house system and platform data, HSTYLE set up the M of the new data-driven product testing routines.

However, the data testing routines were met with resistance from the Product Department and the Marketing Department. The fundamental reason was that the business departments believed that the data departments, by using big data analysis, had taken over the mandate of product testing. Loss of the testing mandate would prevent the directors, managers and supervisors of the business departments from directly deciding which products get more production and marketing resources, and thus might affect the remuneration distribution within the departments. As the conflict arose from the redistribution of mandates, rather than from technological backwardness or value misconceptions on the part of those business departments, HSTYLE identified this type of conflict as a power conflict.

Faced with this power conflict arising from data embedded product testing, HSTYLE adopted an active adaptation mechanism in response. Case data showed that HSTYLE's active adaptation referred to a problem-solving mechanism that simultaneously adopted multiple adaptation strategies to align the M of big data system with product testing routines, and then selected an optimal one from among them. To be specific, HSTYLE selected some brands for data-driven product testing, while other brands were still subjected to traditional EB product testing, and then compared the performances of the different programs. During the implementation of the data-driven product testing program, the PMP departments could have discussions and consultations on the data dimensions, data weights, and algorithms, which could lead to regular adjustments in light of the discussion outcomes.

The core reason why HSTYLE adopted an active adaptation strategy for power conflicts was that the degree of resistance generated by power conflicts was of intermediate level. On the one hand, the heads of the business departments were resistant because of the loss of product testing mandate and responded negatively to the data-driven testing initiative. But on the other hand, the mid-level management and grassroots employees in those departments were eager to see more objective and fair results from the new data-driven testing program. Accordingly, the executive team of HSTYLE opted for the active adaptation mechanism based on the actual resistance level and the dynamics underlying it. Through the open comparison of various programs, the organization members voluntarily opted for the data-driven product testing. Table 3 presents typical evidential incidents in the identification and resolution stage of the data-related conflicts.

Table 3 Evidential Incidents of Identification and Resolution of Data Conflicts

Organizational routines	Change measures	Evidential incidents (typical citations)
Data embedded in product planning	Technical conflicts identification	"We hope that data will tell us what kind of products to produce, when they are to arrive, and when to place reorders. Through data management of the entire life cycle of PD, we can systematically make the entire operation rhythm healthier and more rational. However, between 2013 and 2015 the data provided by the Planning Department was very inaccurate and not instructive."
		"A typical example is that in 2013, the Planning Department calculated a relatively safe and reasonable wool production quantity based on big data, but the PMP departments thought this plan was inaccurate, so they arbitrarily enlarged the production quantity. The senior executive team was furious when they find it out."
	Passive adaptation	"The senior management team gives the Planning Department the review power of product planning, which leads to a fundamental change in the product planning process. In the past, the Planning Department sends the data planning results to the Product Department, which could ignore the report and place orders directly. Now, the Product Department cannot do that. They can only execute the single program [recommended by the Planning Department]."
	Value conflicts	"In traditional concepts, clothing is a typical non-standard product, emphasizing the designers perceptual understanding, which makes it difficult to speculate on the so-called trend, fashion, and color based on rational data, algorithms, and models. Therefore, you need to rely on the empirical judgment of product designers and buyers."
Data embedded in product design		"The product team seldom designs products based on data. When it comes to data that have a relatively large impact on the products, designers and buyers could not easily accept it, because once it is applied, it might have a negative impact."
	Alignment	"In the beginning, the Product Department had difficulty in the application of the data, so the senior management team of HSTYLE refrained from imposing it. They required that designers and buyers shall read the data reports, and then look at the actual results after a period of time to see for themselves whether the results were consistent with the insights gained from the data."
		"At the same time, communications between the Planning Department, the Data Intelligence Department and the buyers of the Product Department become more frequent, and the real needs of the designers in the design process are captured by this in-depth liaison; their needs are then reflected in the optimization and improvement of the data system. "

(*To be continued*)

(*Continued*)

Organizational routines	Change measures	Evidential incidents (typical citations)
Data embedded in product testing	Power conflicts	"We hope to solve this problem through data, that is, to focus on the production and sales of the products that can generate the most profit, the most gross profit, and the most sales. But we find that the Product Department is very resistant, and the corporate acceptance at the time is very difficult."
		"The manager of the Product Department feels that things that could once be decided after a discussion among a few of our managers and supervisors in the past must now be arranged by the Planning Department, which would take away their power in product testing, and would affect the control of the director of the Product Department over his subordinates and his position in the company."
	Active adaptation	"The Planning Department makes concessions at that time, and only selects some brands for data-driven product testing at the initial stage, that is, using data to determine which products get more resources while most brands still go through the traditional product testing routines. If the Product Department thinks that the data calculation of the product testing are not accurate, we would discuss the specific algorithm."
		"The Planning Department is very good at 'reckoning after the fall' as the saying goes. All products that are reordered by the Product Department based on experience are recorded. In the end, it is found that 80% of the reorders based on manual experience should not have been made at all."

4.2.2 Stage of Acceptance and Enhancement of the ROD (2016–2019)

In the process of using adaptive strategies to resolve data-related conflicts in product planning, design and testing routines, the agents' actions of different organizational routines (P) interact and mutually align with the characteristics of the data system (M), and finally produce an objective rule (O) that can be accepted by different departments. We will call this the rule of data (ROD) acceptance link, which is defined as the process by which different actors within an organization adopt the DDPD system. It is noteworthy that from 2014 to 2016, HSTYLE's product sell-out rate was as high as 95% for three consecutive years, which reflected the positive impact of big data on the accuracy of PD and directly accelerated acceptance of the ROD. On the basis of the acceptance, the data departments continued to promote the transformation of the material part (M) through innovation of O and P. We called this link the ROD enhancement, which was defined as the process in which different agents within an organization strengthened and improved the DDPD system.

Data-driven product planning: Passive acceptance and data asset enhancement. Enforcement of big data-driven product planning routines imposed the ROD on the business units. As the director of the Planning Department said: "It is not necessarily correct to act according to the data plan of the Planning Department, but if you don't follow my plan, I wouldn't even have a chance to know if I'm right or wrong." When the business

departments gradually saw eye to eye with the data-driven new product plans, HSTYLE lost no time in making changes in the product planning business process, and consolidated it in the form of corporate institutional process. At the same time, the new data-driven product plans had certain flexibility in them, which allowed the Product Department and the Marketing Department to tweak within a certain range based on their experience.

In 2017, after a period of time during which data-driven product planning routines were implemented, the HSTYLE management team realized that there was no longer room for improvement on the accuracy of data-driven new product planning. The core reason was that the data dimension of new product planning was limited to commodity data. In order to further improve the performance of the new data-driven product planning, HSTYLE decided to enhance its data assets. Specifically, HSTYLE began to, through the Planning Department and the Information Center, built the customer relations management (CRM) system to capture data on consumer behavior, the supply chain management (SCM) system to capture supplier data, the industry analysis (IA) system to capture competition data, the marketing management (MM) system to capture events data.

The enhancement of big data assets directly led to innovations in the actions of the agents of product planning routines. A typical example was the Sophon project which was a joint effort of the Data Intelligence Department and the Information Center in 2018. The project was based on HSTYLE's nearly 10 years of massive amount of consumer data and the original product planning algorithm, which could be used to precisely forecast product sales one month before any platform event, providing important technical support for short-term product planning. After a period of execution, the Planning Department, the Data Intelligence Department and the Product Department formulated the new O: For the top-ranked mature models, the planning results of the AI algorithms were far better than the previous manual predictions, so Sophon was used for the planning of those products; for products ranked in the middle and lower regions, AI algorithms needed to be fine-tuned manually to achieve better results and so a hybrid planning process was adopted.

Data-driven product design: Active acceptance and enhancement of data awareness. Big data-based product design routines were not imposed, but through incremental alignment. The data system was gradually aligned with the design behavior of product buyers. On the one hand, the Product Department not only had established data thinking, but also significantly improved its understanding of data. From front-line employees to department directors, all gradually learned to speak in terms of data; on the other hand, the Product Department directly helped the data system improve its analysis dimensions. For example, the Product Department guided the Planning Department and the Information Center in their effort to obtain consumer preferences for and recognition of brands based on years of its operational experience. In this way, on the basis of gradual alignment of M with the behavior of the product buyers, HSTYLE's Design Department voluntarily accepted the data-driven design rules, and established the new O in the form of institutionalized corporate regulation: In the process of product design, the Product Department needed to communicate with the Planning Department and the Data Intelligence Department to jointly implement the design business process; the data departments provided design-related data support for the Product Department, and influenced its design direction according to market demand and preferences.

Based on the active acceptance of data-driven design routines, the Data Intelligence Department began to further enhance the data awareness of the Product Department in early

2017. Specifically, first, the Data Intelligence Department, with the support of external professional organizations, trained the buyers of the Product Department so that the buyers could finely subdivide clothing styles into elements which were digitally tagged. Second, the Data Intelligence Department combined tagged elements with external consumer data to help the Product Department predict target audience's purchase intentions for a particular product.

On the basis of the enhanced data awareness of the Product Department, data-assisted product design was transformed into data-driven product design, which was apparent in that before designing any product the product team would take the initiative to ask the Data Intelligence Department for the analysis report of the trend forecasting data. The product director stated thus: "Founders of the corporation have been promoting the Group's long-term strategy as take root in the apparel industry and build AI-driven capabilities based on the whole chain, which inspire us to attach great importance to the application of data in design." Eventually, HSTYLE established the M of data-driven product design at the institutional level: The Data Intelligence Department shall, before development of any clothing, provide the Product Department with analysis on the fashion trends and consumer preferences; the Product Department designed clothes according to the analysis report; and all product design decisions were to be made on data-based judgment and sensible perceptions.

Data-driven product testing: Active acceptance and enhancement of data analysis. Active alignment of big data-driven product testing routines ultimately made the business units voluntarily accept data-based testing rules. Two main reasons accounted for this: First, with the gradual improvement of data analytics, the new product classification done by big data far outperformed EB product classifications in terms of sales; second, although the mandate of the Product Department and the Marketing Department in testing had been weakened, they could indirectly influence the criteria and direction of product testing through their discussions and consultations with the data departments on the dimensions of data analysis and data weight, and thus attenuating the power conflict between the data departments and the business departments.

In 2017, after the routines of data-driven product testing were implemented for a period of time, the Planning Department and the Data Intelligence Department found that data analytics directly determined the efficiency of product testing and decided to further enhance data-driven product testing routines through data analysis. First, the Data Intelligence Department referenced advanced machine learning algorithms both in China and abroad, and adopted more sophisticated algorithms to improve the product testing process. Second, HSTYLE developed its proprietary intelligent reordering, intelligent pricing, new item stocking scheduling and other algorithms in key areas. Through accumulated data and iterative execution of the algorithms, core competitive advantages of the enterprise were created. With the support of big data analytics, product testing routines did not require manual intervention or tweaking during the execution process, which was truly automatic in resource allocation based on data and algorithms. This automated flow helped HSTYLE achieve high sell-out and turnover rates in the rapidly changing internet market. Finally, HSTYLE restructured the O in data-driven product testing routines: The PMP departments confirmed the algorithms provided by the Data Intelligence Department and the Planning Department, and the latter two carried out the product testing and place reorders. The reordering process tried to avoid manual intervention. Evidential incidents for the stage of ROD acceptance and enhancement are shown in Table 4.

Table 4 Evidential Incidents for the Stage of ROD Acceptance and Its Enhancement

Organizational routines	Change measures	Evidential incidents (typical citations)
Data-driven product planning	Passive acceptance	"After everyone begins to agree with the [data-driven] planning, we quickly update the corporate business process to reflect the change.... Every day, when the Product Department decides to place an order, we review it."
		"For example, if there is a value of 10 million yuan, you can't place 12 million, and you can't place 8 million either, but you can place 10.05 million, and you can place 9.95 million. We still allow a certain amount of flexibility."
	Data asset enhancements	"In 2017, I suddenly discovered that all our data was just commodity data, and it was impossible to establish a close-loop data-based operation process. The data shall be multi-dimensional, so that our business planning could be more accurate."
		"On Double Eleven in 2018, we officially launched the AI planning system Sophon. Through this system, we planed the number of product sales on Double Eleven, so as to guide downstream product design and product testing."
Data-driven product design	Active acceptance	"In the past, the Product Department used to rely only on experience to speculate on the styles in the process of product selection. Now it will refer to the previous sales data and the data analysis provided by the Planning Department. Otherwise, it will be difficult to convince the Marketing Department, Production Department and other departments to believe that the clothes will be easy sells."
		"In the past, the designing [team] did not look at data, but now the process stipulates that the Planning Department, Information Center and Marketing Department will systematically report the results of big data analysis to the Product Department, and influence the product design direction of the product team according to market demand and consumer preferences."
	Enhancement of data awareness	"The Data Intelligence Department subdivides the style of a piece of clothing into a series of finely-grained elements such as cuffs, colors, and patterns, and tags the elements. All the tags are put together to form the style."
		"Our design is now based on consumer needs, that is, through online data, we ask countless consumers what styles they like, and let the various data from them guide the design."

(*To be continued*)

(*Continued*)

Organizational routines	Change measures	Evidential incidents (typical citations)
Data-driven product testing	Active acceptance	"Even in cases where the HBSN algorithm is relatively perfect, the Planning Department will still give some leeway to the Product Department, which can apply for reorders according to the actual situation, even if some of the products are on the stagnant list, which ensure flexibility and stability."
		"For the problem of the HBSN algorithm, we have established a work communication window. Only during the window period can the algorithm be modified to establish the logic for placing reorders."
	Data analytics	"On the basis of all business data, technical improvements are made through machine learning, which makes the HBSN algorithm more accurate. For example, Natural Language Processing (NLP) evaluation analysis, we also use this method to incorporate users' online reviews into the testing algorithm."
		"The total amount, growth rate, and increased amount etc. used in the past are too crude to reflect the history and current status. We now use the current popularity, the number of days on shelf, and seasonal factors for the calculations, which is more accurate."
		"For all e-commerce operations and data-related content, such as smart reordering, smart pricing, and restocking optimization, we accumulate data and develop our proprietary algorithms, which is the core competence of our company."

4.3 After the DDPD Transformation

After transforming to DDPD, the connotations of product planning routines, product design routines and product testing routines have changed in substance, featuring characteristics of data-driven management decision-making. The following explanation uses the example of data-driven product testing routines shown in Figure 2.

The data-driven product testing routines consist of five steps. First, the Planning Department determines the ratio of initial orders to reorders from the perspective of operations planning data; the Production Department, after confirmation of the ratio, places an order for production (processes ① and ② in Figure 2). Second, the PMP departments after referencing the rhythm of platform activities put forward initial orders for new items (processes ⑤ to ⑦ in Figure 2); the Planning Department and the Data Intelligence Department conduct data tracking and analysis during the sales of the initial orders (processes ③ and ④ in Figure 2). Third, the Planning Department, the Data Intelligence Department, and the Information Center evaluate the efficiency of the initial orders according to the HBSN algorithm, to get the testing results (processes ⑧ to ⑩ in

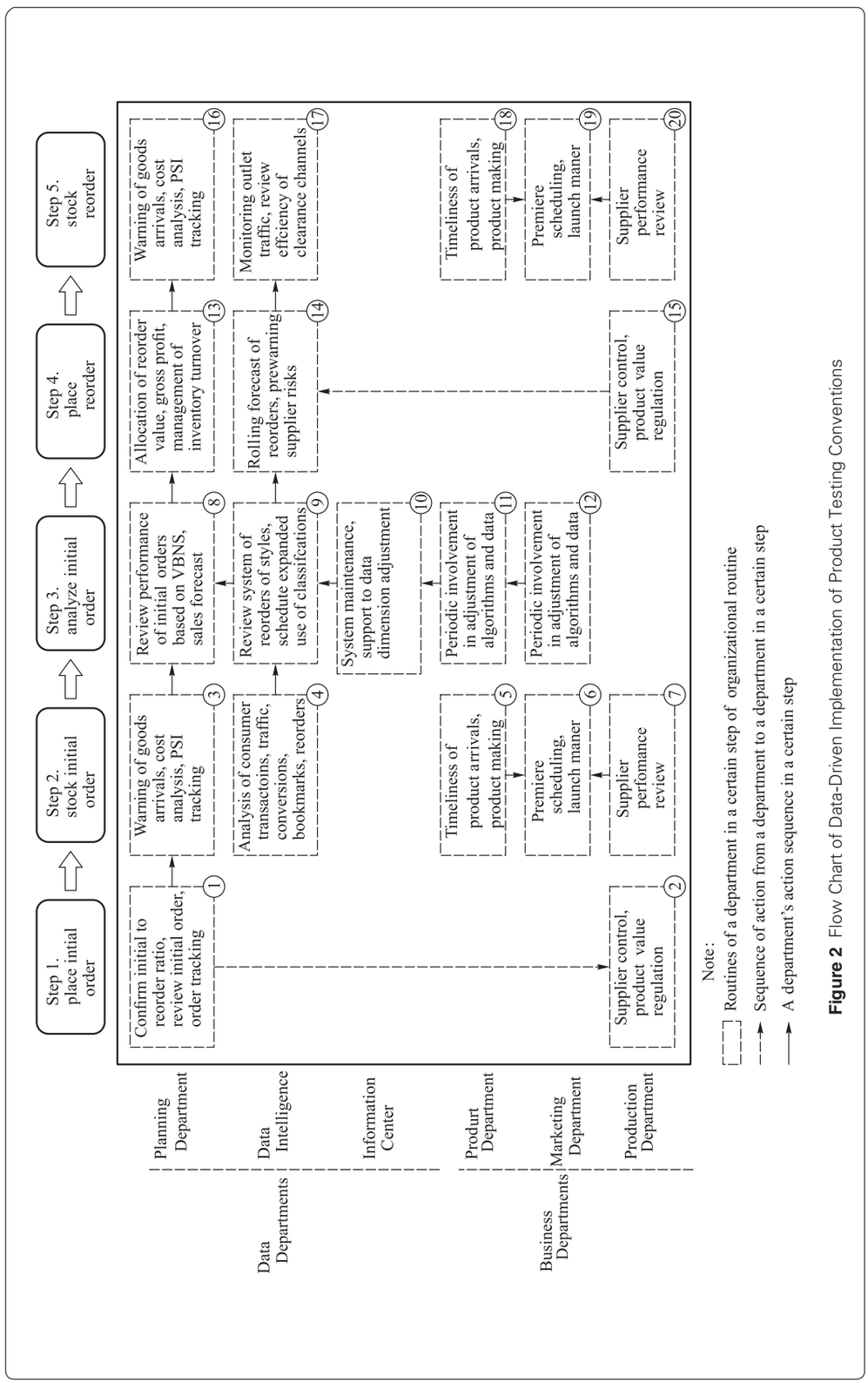

Figure 2 Flow Chart of Data-Driven Implementation of Product Testing Conventions

Figure 2); the Product Department and the Marketing Department furnish their opinions and suggestions on the algorithms and data dimensions (processes ⑪ and ⑫ in Figure 2). Fourth, the Planning Department and Data Intelligence Department calculate value allocation for reorders based on the testing results, and they also advise the suppliers on their capacity risk based on relevant algorithms; the Production Department accepts the order and sets about production speedily (processes ⑬ to ⑮ in Figure 2). Fifth, the Marketing Department, Product Department and Production Department update the reordered products (processes ⑱ to ⑳ in Figure 2). The Planning Department and the Data Intelligence Department track and analyze the sales status of the reordered products, and evaluate the performance of them (processes ⑯ and ⑰ in Figure 2).

Comparison of Figures 1 and 2 reveals that differences exist between data-driven product testing routines and experience-based product testing routines in all the five steps. Take Step 3 of the testing routine or the analysis of the initial order as an example. Before the transformation, the efficiency of the initial order is mainly evaluated by the Product Department and the Marketing Department based on experience. After the transformation, the testing is transferred to the data departments such as the Planning Department, the Data Intelligence Department and the Information Center; efficiency evaluation is carried out by the data departments while the business departments only participate in the refinements of the algorithms and data dimensions on a regular basis.

Comparing Figure 1 with Figure 2, it can also find that, data-driven product testing routines are different from the EB ones in development risk, decision rationality and collaboration costs. First, in terms of development risk, EB product testing programs mainly depend on the experience of each department, with high uncertainty; in contrast, data-driven product testing is based on consumer transaction and communication data, industry competition data, etc. to anticipate styles that consumers may like. This reduces the individual empirical biases of the designers in the PD process.

Second, in terms of decision-making rationality, PD decisions of the Product Department are often based on satisfying their own interests and are prone to short-term irrational behaviors. In data-driven product testing, however, the testing mandate is transferred from the business departments to the data departments, which helps the enterprise establish refined management and control of the entire PD process, reducing the impacts of the irrational behaviors of the business departments. Finally, in terms of collaboration cost, in the EB product testing routines, the PMP departments could only achieve balances through long discussions among themselves while in data-driven product testing, each product testing decision is supported by data records and analysis results. When there are conflicts of interest or disagreements, consultations can be conducted with the help of data results, which effectively reduces the collaboration cost of different departments. As the situations of the planning and design routines are similar to that of product testing, discussions of them are omitted here.

5 Discussions

Research findings indicate that transformation from EBPD to DDPD involves two stages—the data conflict identification and resolution stage, and the ROD acceptance and enhancement stage.

During the data conflict identification and resolution stage, enterprises identify conflicts

arising from data embedded in different PD routines, the conflicts being technical conflicts, value conflicts and power conflicts. Depending on the different types of conflicts, the enterprise takes active adaptation, passive adaptation and mutual alignment strategies. In the ROD acceptance and enhancement stage, a passive acceptance strategy is adopted for the data-driven product planning routines whose O is innovated by data asset enhancement. At the same time, for data-driven product design routines, an active acceptance strategy is adopted and data awareness enhancement is used to innovate the O in product design. Finally, an active acceptance strategy is adopted for data-driven product testing routines whose O is enhanced by data analytics. Thus, the transformation from the data conflict identification and resolution stage to the ROD acceptance and enhancement stage forms. This DDPD transformation path and implementation mechanism framework are shown in Figure 3.

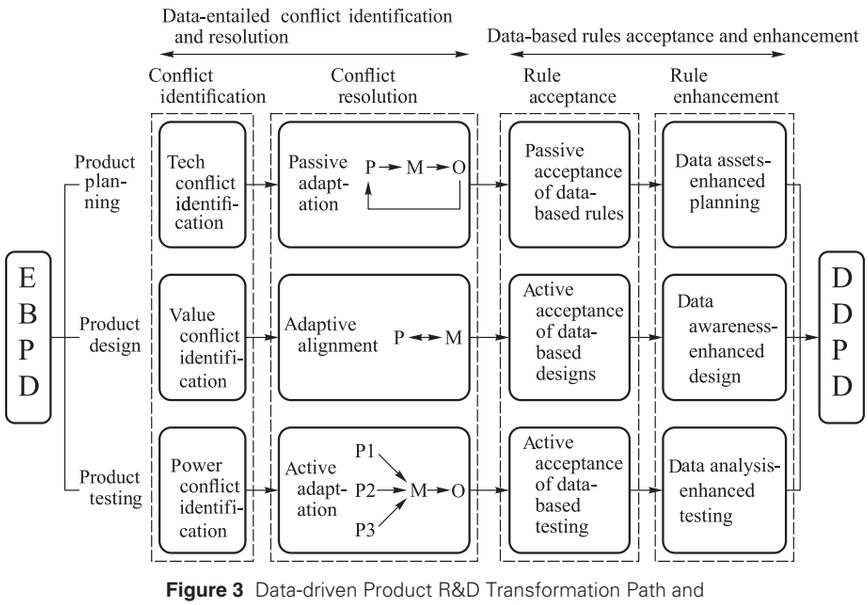

Figure 3 Data-driven Product R&D Transformation Path and Implementation Mechanism Framework

5.1 Two-Stage Transformation Path of DDPD

Extant research on planned organizational change mainly describes the path of organizational change with the multi-stage, linear relationships and combined logic model (Al-Haddad & Kotnour, 2015), such as the classic three-stage organizational change path model-preparation, transformation and solidification (Lewin, 1951) and the six-stage IT implementation process model developed from the perspective of technology diffusion — initiation, adoption, adaptation, acceptance, routinization, and integration (Goh et al., 2011).

In view of current literature on the model of transformation stages, the data conflict identification and resolution stage in this case roughly corresponds to the organizational change initiation, implementation and resolution stages. The adaptation stage and the ROD acceptance and enhancement stage roughly correspond to the organizational change realization, routinization and institutionalization stages. However, the above-mentioned

multi-stage linear change model ignores the impacts of key contingency factors, making this type of stage model difficult to apply to different organizational change situations (Burgelman et al., 2018; Weick & Quinn, 1999). It is also difficult to apply to the transformation from EBPD to DDPD. The difficulty mainly lies in two situational changes.

First, the extant transformation stage model emphasizes that the transformation path is generally a planned path — preparation, process and termination. This kind of model has more explanatory power for upgrading from low-level to higher-level manufacturing, like from Original Equipment Manufacturer (OEM) or Original Brand Manufacturer (OBM) to Original Design Manufacturer (ODM) (Kang et al., 2016), but data-driven PD transformation is a transformation from human or organizational experience-based decision-making to hybrid decision-making of human-machine collaboration with higher uncertainty and more complexity than the manufacturing transformation or upgrading path. Therefore, it is difficult to explain by the extant multi-stage, linear relationship and combined logic model.

Second, extant models of transformation stages often see initiation, preparation or unfreezing as the first step in the transformation, which is reasonable in most cases, but this multi-stage linear change model appears to set change in a pre-determined, controllable, predicted state, where change becomes an approximate command-control strategy (Girod & Whittington, 2015). However, from the findings of this paper, it is clear that when data is embedded in the PD process, various conflicts arise. The organization has to be quick to meet the management challenges by resolving the conflicts without initiation, preparation or unfreezing. These conflicts arising from data embedding indicate that data-driven organizational change needs to face the impact of contingency factors all the time. It therefore makes more general sense to revisit and redefine the first stages of transformation from the perspective of conflicts in change. Accordingly, this paper proposes a two-stage path model for DDPD transformation.

Authors believe that the transformation from EBPD to DDPD goes through two stages—the first stage of conflict identification and resolution, and the second stage of ROD acceptance and enhancement. The two-stage path model of DDPD transformation combines the theory of planned organizational change with key contingency factors and emphasizes that the path of DDPD transformation has both the linear characteristics of two stages, and the impact of key contingency factors resulting from the uncertainty and complexity of human-machine collaboration in decision-making in a data-driven situation. For example, at different stages of a data-driven organizational change, enterprises can adopt different conflict resolution and institutional innovation as they embed data into various organizational routines. Therefore, this two-stage DDPD transformation can provide contextual explanations for the DDPD transformation process, advancing the study of the intersection of planned organizational change and contingency factors.

5.2 The Realization Mechanism of DDPD Transformation

Breakthrough innovations in technology, major shifts in the competitive environment, and consumer empowerment typically constitute the three external drivers of organizational change (Huang et al., 2017). The findings of this paper show that the transformation of an enterprise from EBPD to DDPD is closely related to these external drivers, especially integration of the internet, big data, AI and other new-generation information technologies

with PD processes. This deep integration drives an enterprise to DDPD. In this case, the key realization mechanism for the transformation from EBPD to DDPD lies in how to transition from conflict resolution in the first stage to ROD acceptance and enhancement in the second stage. To be specific, how the three conflict resolution mechanisms in the first stage transition to the three ROD acceptances and enhancements in the second stage. By dissecting this transition process well, the specific connotation of the DDPD implementation mechanism can be extracted.

Previous studies have mainly explored the realization mechanism of organizational change from the perspectives of organizational routines, organizational learning, or dual competencies (Tushman & O′Reilly, 1997). This paper posits that in the DDPD transformation process, the embedding of big data resources into different PD routines will trigger different data-entailed conflicts, and it is necessary to adopt an adaptive organizational routine change as the realization mechanism (Sun et al., 2019). On the one hand, existing organizational routines or organizational learning perspectives emphasize that firms adopt a single approach to change for different routines at the same time (Pentland & Feldman, 2008). In contrast, this paper emphasizes that the DDPD transformation realization mechanism is an adaptive change mechanism based on different organizational routines, and believes that enterprises should adopt an adaptive realization mechanism, from intermittent to balanced, according to the characteristics of different organizational routines. This is in line with the requirements of the six-element cycle of adaptive management, namely problem definition, program design, implementation, monitoring, evaluation and management improvement (Murray & Marmorek, 2004). On the other hand, the existing dual competences realization mechanism focuses on the dynamic balance process through which enterprises balance external conflict pressures (Albert et al., 2015), while the adaptive change mechanism of organizational routines proposed in this paper focuses on the dynamic ability of enterprises to balance internal transformation conflicts. The two are applicable to different organizational situations.

Specifically, in the conflict resolution stage, extant research in the implementation field of enterprise information system believes that the mismatch between information technology and organizational routines will entail a series of conflicts in the enterprise, which are often manifested as technical conflicts (Wei et al., 2005), value conflicts (Allen, 2005), and power conflicts (Scott & Wagner, 2003). Enterprises have the options to adopt passive adaptation mechanism, active adaptation mechanism and mutual aligning mechanisms in response to the data-entailed conflicts of different PD routines, which can effectively deal with the organizational and individual resistance to data applications. Similarly, in the ROD acceptance and enhancement stage, the enterprise adopts passive acceptance and data asset enhancement for the product planning routines, active acceptance and data awareness enhancement for the product design routines, and active acceptance and data analytics enhancement for product testing routines. In this way, the P, the O and the M of different PD routines are successfully transformed through the adaptive change mechanism. Specifically, in the change of product planning routines, a transformation mechanism from the passive adaption approach for conflict resolution to passive acceptance of M is established; in the change of product design routines, a transformation mechanism from conflict resolution through mutual alignment to active acceptance of data-driven design is formed; in the change of product testing routines, a transformation mechanism from active adaptive conflict resolution to active acceptance of the O of data-driven testing is set

up. In particular, typical adaptive management mechanisms are adopted for both product planning routines and product testing routines, while the acceptance of ROD for the three organizational routines fully reflects the characteristics of adaptive management (Vergne & Depeyre, 2016).

First, in the adaptive change of product planning routines, as the data systems are general-purpose, the mismatch between organizational routines and system functions often leads to technical conflicts (Strong & Volkoff, 2010). A technical conflict refers to the negative impact that arises when the technical functions of an enterprise information system do not meet the operational objectives of the enterprise (Scott & Kaindl, 2000). The findings of this paper not only reproduce the technical conflicts in digital transformation, but also further point out that enterprises can use passive adaptive management to solve technical conflicts because technical problems need to be solved in specific implementation plan, emphasizing the trial-and-error learning in DDPD transformation. The case study of iterative adjustment of organizational routines from an adaptive change perspective on the importance of resolving technical conflicts confirms the findings of Soh et al. (2003). In general, the alignment of O with M in organizational routines is not a prerequisite in passive adaptive management (Sia & Soh, 2007). Instead, enforcement of M in situations of misalignment is emphasized. Berente et al. (2016) propose that system value can be realized through the enforcement of information systems in cases of persistent misalignment between systems and organizational routines. In addition to further enriching the above viewpoints, this paper finds a link between the realization mechanism of DDPD transformation with the technical conflicts, clarifies how the passive adaptation mechanisms solve the technical conflicts caused by data embedding, and promotes mutual alignments between organizational routines and technological changes.

Second, in the adaptive change of product testing routines, when the data departments as low-power entities find it difficult to obtain the support of the business departments, power conflicts arise (Scott & Wagner, 2003). Power conflicts refer to the negative impacts that may lead to the redesign or adjustment of the power structure of each agent in the business process during the application of an enterprise information system (Davenport, 2000). This case study finds that active adaptive management can effectively solve the power conflicts faced by product testing routines because different departments can propose their own rules for the execution of the routines based on their own interests, but performance comparisons of different programs can be done during the implementation process. Results of the comparisons can reduce disputes caused by power conflicts. This finding underscores the point made by Kim and Kankanhalli (2009) on how to resolve power conflicts between business and information departments through mutual adaptive adjustment. At the same time, this case also confirms a similar point put forward by Markus and Tanis (2000) from the perspective of digital transformation.

Finally, in the adaptive change of product design routines, this case study has revealed a third conflict resolving mechanism in addition to passive adaptation and active adaptation-mutual adaptive alignment, which is similar to natural selection in the organizational adaptive growth model (Harrison, 2004). Different from passive adaptation to enforce a single plan and active adaptation to execute multiple plans simultaneously, mutual adaptive alignment refers to a problem-solving mechanism for a situation in which when the management decision-making plan is not implemented, the enterprise gradually persuades the actors to understand and accept the management decision, and finally accomplishes

an adaptive alignment (Strong & Volkoff, 2010). It is true that among the three adaptive change mechanisms, the change of product design routines is achieved through a conflict resolution of mutual alignment mechanism which results in the active acceptance of the ROD in product design, rather than a standard adaptive management mechanism. It also reflects from one aspect the complexity and diversity of adaptive mechanisms for DDPD transformation. Extant research shows that the implementation of information systems such as ERP will give rise to value conflicts within the enterprise. Value conflicts refer to the negative impacts brought by the mismatch between the internal management logic in the use of information systems and the enterprise's work priorities, work dependencies, and work evaluation criteria (Lamb & Kling, 2003). In this case, there is also a conflict of values caused by data embedding, which is apparent in the conflict between the rational judgment of the data-driven approach and the subjective perceptions in product design. The adaptive realization mechanism of DDPD transformation points out that the best way to resolve the value conflict caused by data embedding may be mutual adaptive alignment, rather than active or passive adaptive management. This is an important viewpoint and conclusion of the adaptive realization mechanism in DDPD transformation. It proposes a new organizational adaptation concept to resolve value conflicts, enriching the connotation of adaptive change in organizational routines in the digital transformation of enterprises.

5.3 The Theoretical Model for DDPD Transformation Paradigm

On the basis of the above discussion on the two-stage path and realization mechanisms of DDPD transformation, this paper further proposes a theoretical model for the DDPD transformation paradigm shown in Figure 4 based on the case findings and literature.

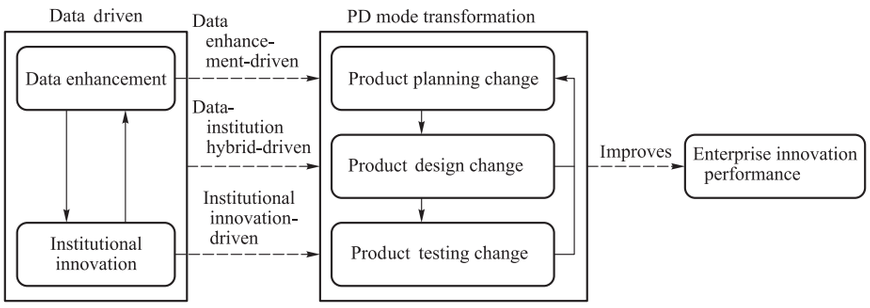

Figure 4 Theoretical Model of Data-Driven Product R&D Transformation Paradigm

Extant research usually describes data-driven as a data-enabled management decision-making model, such as that data-driven is the way that enterprises optimize and deal with management decision-making problems by collecting, acquiring, analyzing and using data (Xu et al., 2016), or data-driven is defined as a dynamic process in which an enterprise promotes the performance of its operations and management through big data resources and improves the co-evolution ability of enterprises and ordinary consumers (Sun et al., 2019). In Figure 4, this paper further proposes that in the context of big data-enabled PD

made transformation, the core connotations of data-driven include data enhancement-driven PD transformation, institutional innovation-driven PD transformation, and data-institution hybrid-driven PD transformation. The three aspects of the connotation of data-driven embody three dimensions in the context of PD transformation as follows.

First, extant research emphasizes that under the data-driven management paradigm, the embedding and enhancement of data technology can change the decision-making path of enterprise management, and ultimately help enterprises accomplish data-enabled innovation (Chen et al., 2018), which in this paper is called data enhancement-driven, and is defined as the process by which an enterprise changes its management model by continuously enhancing the level of data technology utilization. However, extant research has not conducted in-depth research on the conflicts caused by data technology embedding. The theoretical framework in Figure 3 fills this research gap, and Figure 4 further emphasizes that the embedding and enhancement of data technology can indeed improve and enhance the decision-making process of PD management, but data enhancement-driven is only one of the manifestations of being data-driven. For example, the enhancement of HSTYLE's product testing routines shows that improving data analytics can improve the performance of data-driven product testing. The findings of this paper confirm the above point, but it should be emphasized that the content of data-driven is not limited to the enhancement of data technology.

Second, extant research emphasizes that being data-driven is not a complete replacement for institutional innovation[3] generated by empirical practice, but a necessary complement (Sorescu, 2017). Here, institutional innovation-driven in the context of DDPD transformation refers to the process in which an organization accumulates experience through implementing big data activities, or changes the DDPD model by learning data analytics from external partners. Taking the continuous change of product planning routines as an example, organizational members continue to accumulate experience in the process of implementing data planning, prompting organizational members to recognize the need to use more dimensions of big data to improve planning performance. Therefore, this kind of institutional innovation does not come from the understanding of leading technology, but directly from the demand for institutional innovation in data planning behavior and experience, which is consistent with the path of institutional innovation in the non-big data context. It can be considered that being data-driven has not replaced the transformation path of institutional innovation-driven PD, and institutional innovation-driven can be regarded as one of the manifestations of being data-driven.

Third, being data-driven emphasizes the deep integration of big data analytics and institutional innovation for PD, and the two influence each other to promote the transformation and upgrading of PD (Autio et al., 2018; Xie et al., 2018). Hybrid promotion of data system refers to the process in which an organization promotes the change of PD model by improving the utilization level of big data analytics and accumulating data application experience of both internal and external entities. Taking the digital transformation of product design routines as an example, years of market sense and business sensitivity of the product designers are an important basis for the transformation of

[3] While emphasizing the stability of organizational routines, extant research also pays extensive attention to the dynamics and flexibility of organizational routines, and believes that institutional innovation is the core source of competitive edge for organizational routines. It has been emphasized that institutional innovation of organizational routines is to be achieved through alternative learning and experimental learning (Ancona & Bresman, 2007). This kind of literature is very rich and will not be repeated here.

the PD system, and big data analytics can be a necessary complement to the inspiration and wisdom of the designers. Both are indispensable. This results in an interactive and iterative update process that collectively improves and enhances product design routines. This conclusion is consistent with Zhan et al. (2018), emphasizing that the interaction between business and data departments in the context of big data is the key to accomplishing data-driven decision-making transformation. Therefore, the institutional innovation led by the business departments and the technological enhancement led by the data departments interact and promote each other to form one of the three data-driven means of implementation in the model in Figure 4.

Extant research defines paradigms as models and modes of solving specific problems using selected principles of the natural sciences (Dosi, 1982). The theoretical model of the DDPD transformation paradigm proposed in Figure 4 emphasizes that data enhancement, institutional innovation, and the interaction of data enhancement and institutional innovation promote each other, and constitute the three core connotations of DDPD, which influence and reconstruct PD mode as proposed by Wessel (2016). The PD model of an enterprise has undergone many transformations, such as from closed innovation to open innovation, and from technology-driven innovation and market-pull innovation to network cooperation innovation (von Hippel, 1986). The theoretical innovation of the model in Figure 4 is that it highlights the mutual promotion of data enhancement and institutional innovation, which together constitute the key driver for the PD transformation in the context of big data, so that enterprises can transform from EBPD to DDPD which relevant extant research has seriously ignored or lacks in-depth exploration into.

Fourth, the theoretical model of the transformation paradigm in Figure 4 also epitomizes the theoretical framework of the digital participation of ordinary consumers in product innovation proposed by Xiao et al. (2018). It answers the question as to how enterprises can get consumers involved in PD and innovation by using big data. Extant research shows that ordinary consumers can, through big data as a medium, deeply influence enterprise PD models and decision-making mechanisms (Stock, 2014). The conclusion of this paper confirms this point of view, and further emphasizes that incorporating ordinary consumer data into corporate institutional innovation is the key to consumer involvement in PD innovation (Bharadwaj & Noble, 2015). Therefore, the conclusions of this paper provide good theoretical inspirations for enterprises in their efforts to get ordinary consumers involved in their PD.

6 Conclusions

6.1 Theoretical Contribution

This paper, by putting forward the theory of DDPD transformation, and expounding the two-stage transformation path from EBPD to DDPD, the realization mechanism, and the transformation paradigm, is a response to call of Chanias et al. (2019) for further studies of the process of digital transformation. The theoretical contributions are reflected in the following three aspects.

First, extant research on planned organizational change mainly describes the transformation path of organizational change using the combined logic of multi-stage and linear relationship (Al-Haddad & Kotnour, 2015; Lewin, 1951), ignoring the impact of key contingency factors. The two-stage path model of DDPD transformation proposed in this

paper combines the theory of planned organizational change with key contingency factors, emphasizing that there are characteristics of two linear stages in the DDPD transformation path. This conclusion provides a contextual explanation for the DDPD transformation path, and advances the theoretical study of the intersection between planned organizational change process and key contingency factors.

Second, different from extant research that focuses on the realization mechanism of PD transformation in non-big data contexts (Chesbrough, 2003; Foss et al., 2013), this paper proposes the realization mechanism of DDPD transformation from the perspective of integrated adaptive change of organizational routines, and dissects how the P, O and M of different organizational routines transform through adaptive change in the DDPD transformation. This work deepens the theoretical study of organizational routine change and organizational adaptation in which big data affects PD transformation, and fills the theoretical gap in the transformation from EBPD to DDPD.

Third, current big data-driven research usually regards data-driven as a way of optimizing management decision-making based on data, taking it as a situation or an assumption without making any concrete expositions (Xu et al., 2016). This paper makes an innovative elaboration about the connotation of data-driven in the context of PD transformation and believes that data enhancement-driven, institutional innovation-driven, and the data-institution hybrid-driven are the three core components of being data-driven. Among them, the mutual impact between data enhancement and institutional innovation reflects the complex nature of human-machine collaboration in the DDPD transformation. This conclusion fills the gap in the research which lacks specifics on big data-driven management decision-making.

6.2 Practical Implications

Big data applications provide enterprises with new competitive edges, but also pose challenges to the original organizational resources, processes and structures (Salovaara et al., 2019). How to transform from experience-based management decision-making to big data-driven management decision-making has become one of the practical problems faced by enterprises in recent years (Grover et al., 2018). At the same time, if the OT is too radical, it will easily lead to a decline in the organization's willingness to adopt, and if it is too slow, it will easily reduce data analytics to mere formality. How to balance radical restructuring and incremental adjustments of an organization is also a practical challenge and a management pain point faced by enterprises in the process of digital transformation. This paper can provide the following inspirations for the digital transformation of enterprises, especially in their digital innovation practice in PD.

First, DDPD transformation conflicts can be better resolved through adaptive changes in organizational routines. Due to the difference in the characteristics of organizational routines, different are conflicts arising from different organizational routines when data is embedded in them. Therefore, enterprises first need to fully understand the different attitudes and responses of the actors to data analytics in organizational routines, and different adaptive strategies are to be adopted accordingly.

Second, in the context of big data, continuous adjustment of organizational routines mainly relies on big data updates, which can be continuously improved in three aspects: improvement of data assets, improvement of analytical tools and the cultivation of data

awareness. Specifically, continuous improvement in product planning routines can be achieved through the expansion and update of data dimensions; continuous improvement of product design routines can be achieved through enhancing designers' data awareness; improvement in testing routines can be achieved by introducing data analytics and improving product classification accuracy. In short, through mechanisms of adaptive organizational routine change, continuous improvement of DDPD transformation can be achieved.

Third, the DDPD transformation paradigm emphasizes the collaboration between the data departments and the business departments. On the one hand, enterprises need to rely on the data departments to introduce big data analytics to improve PD performance; on the other hand, business departments need to use external learning and iterative trial and error to accomplish institutional innovation. Data enhancement and institutional innovation promote each other, and promote the improvement of the level of human-machine collaboration in PD routines. In the DDPD transformation paradigm, both are indispensable.

6.3 Research Limitations and Prospects

First, the case enterprise selected in this paper is an internet apparel enterprise. Although the degree of digitization of its operations is relatively low compared with the born-digital firms, it is still more digitized than traditional offline businesses. For the DDPD transformation process of a traditional offline enterprises, conclusions may be different from those of this paper. It can be an important direction for future research to analyze the differences in the DDPD transformation in different types of enterprises. Second, in the Research Findings section, this paper identifies three types of conflicts arising from product planning routines, product design routines, and product testing routines respectively using exploratory case study methods. In practice, however, there may be a single organizational routine that generates multiple types of data-entailed conflicts. In the future, the theoretical explanation of the conflict resolution mechanisms can be enriched by examining more cases. Finally, this article is only the beginning of research on digital transformation. An important future task is to conduct empirical studies of the theoretical transformation model proposed in this paper to deepen DDPD transformation research.

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