Integrating machine learning, modularity and supply chain integration for Branding 4.0

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Abstract

While brands use technologies in various ways to improve their performance, they appear to struggle with achieving Branding 4.0 standards. This new generation of brand development has brought an era of hyper-customized experiences to benefit brand performance. With the Branding 4.0 literature still in its infancy, questions remain regarding how brands can maintain their identity while delivering a hyper-personalized customer experience. This study draws on mass customization, artificial intelligence, and supply chain management literature to investigate how three core organizational capabilities and resources—machine learning, modularity, and supply chain integration—helpful in achieving production flexibility could jointly enable companies to transition to and maintain a Branding 4.0 philosophy through more efficient personalization of their product offerings. This paper reports findings from 15 in-depth interviews with top executives from brands, including some Fortune Global 500 companies, in China's garment and footwear industries to provide insights into Branding 4.0 and the possible contribution of machine learning, modularity application, and supply chain integration. Our findings inform a two-tier response strategy and a three-dimensional analytical framework which provide a theoretical basis for operationalizing Branding 4.0 and exploring, through a resource orchestration lens, how brands can respond to the related adoption challenges. Specifically, our findings show how machine learning's data analysis, knowledge conversion, and transmission capabilities could benefit both modular management and supply chain tasks to optimize product co-design processes and timely responses to customers' changing demands.

Keywords: Branding 4.0; Machine learning; Product modularity; Process modularity; Supply chain integration

1. Introduction

The concept of branding emerged when companies started to focus on using their names to create signature products or services and to distinguish themselves from their competitors. That period was recognized as the Branding 1.0 era (Fournier & Avery, 2011; Isarabhakdee, 2016). Managerial focus subsequently shifted to creating and maintaining a unique brand image through a company's products and services. Those were the core principles of Branding 2.0 (Chan-Olmsted & Shay, 2015). During the Branding 3.0 era, brand managers focused on social responsibility and establishing their brands' social image (Isarabhakdee, 2016; Kotler et al., 2019). Managers are now trying to understand the Branding 4.0 concept of brand–customer cooperation to view customers as a part of the brand. Specifically, under Branding 4.0, brands treat their customers as individuals and consider their personal needs while ensuring the use and delivery of brand elements (Suthar, 2015; Wallace, 2018; Van & Hieu, 2020). Previous research has shown that brands successfully entering the Branding 4.0 stage can benefit from enhanced brand performance in terms of increased customer loyalty, long-term brand competitiveness, and profits (Isarabhakdee, 2016; Hedden, 2020; Wallace, 2018). Yet the Branding 4.0 literature is still in its infancy, and how brands can ensure the conveying of brand elements while delivering a hyper-personalized customer experience still needs to be explored.

Branding 4.0 has brought about a shift from branding being dominated by managers to being jointly created by brands and consumers, i.e., consumers have changed from being brand adaptors to partners. Research shows that co-design activities are an important part of providing a personalized customer experience (Lee & Chang, 2011; Aichner & Coletti, 2013; Yoo & Park, 2016), which is a core aspect of Branding 4.0. Some managers suggest that customer participation in collaborative product design processes enables them to get a sense of hedonic and creative achievement, thus positively influencing their attitude toward the brand (Merle, et al., 2010; Lee & Chang, 2011). To benefit from these personalization advantages, firms need to engage with technical and managerial innovations that improve their efficiency, flexibility, and responsiveness in producing customized products (Tu et al., 2004). The existing literature points to three core organizational capabilities and resources that are helpful in achieving flexibility during production: machine learning (ML), modularity, and supply chain integration (SCI) (Tu et al., 2004; Liu et al., 2016; Sharp et al., 2018). This paper is aimed at investigating how these three resources could jointly enable firms to transition to and maintain a Branding 4.0 philosophy through more efficient personalization of their product offerings.

Model predictions provided by ML have long been highlighted as a priority for implementation and utilization by decision makers and executives in fields such as healthcare and spacecraft engineering (El Naqa & Murphy, 2015). In recent years, the use of computer systems that apply ML algorithms has been expanded to forecasting customer demand in the marketing domain. ML tools drive 35% of the purchases made by customers on Amazon and 80% of the streaming choices on Netflix (Gomez-Uribe & Hunt, 2015; Krawiec, 2018; West et al., 2018). ML has helped their managers to make subtle recommendations to consumers using the websites. As a result, these websites are recognized as the most preferred streaming and e-commerce websites in the world (Shaw et al., 2001; Syam & Sharma, 2018; Von Krogh, 2018; Kamble et al., 2021).

However, the fact that many managers lack a technical background hinders their decisions to introduce ML and makes it difficult for them to adopt these advanced technologies to achieve Branding 4.0 objectives. Moreover, despite its capabilities for analyzing heterogeneous and multidimensional data and converting them into knowledge, ML and the advantages it can bring, particularly for brands in their Branding 4.0 stage, require further research.

Some literature suggests that modularity enables companies to implement customization on a large scale (Tu et al., 2004, Wang et al., 2014; Sturgeon 2002; Fixson & Park, 2008; Seyoum, 2020). Modularity for customization at the production level refers to the division of a complex system into smaller modules with the aim of examining and utilizing them separately (Tu et al., 2004). Scholars have argued that modularity allows workstations and conveyor units to be added, removed, or rearranged to create different process capabilities (Cooper, 1999; Tu et al., 2004). Brands and manufacturers applying the modularity principle gain great design and production flexibility to handle complex processes (Baldwin & Clark, 2006; Tu et al., 2004; Wang et al., 2018). For instance, adopting product modularity offers enhanced variety in product design via component commonality (Duray et al., 2000), increased product variety, shortened delivery lead times, and improved economies of scope (Ulrich, 1995; Duray et al., 2000). Moreover, modularity makes it easier for customers to customize and update their choices (Tu et al., 2004), and it may lead to user-friendly co-design activities. Therefore, the production-level use of modular applications seems to help brands to achieve their Branding 4.0 goals and should be analyzed in that context.

The third factor that enables production flexibility and, implicitly, may promote the adoption of a Branding 4.0 philosophy is SCI, which refers to a firm's coordination and synchronization of its supply partners (Liu et al., 2016). By shifting from transactional relationships to favoring partnerships and collaborating with large, more advanced suppliers, brands may attain greater agility, source smaller batches, and react faster to emerging trends, markets, and customers (Flynn et al., 2010; McKinsey, 2021). Many companies, especially those in the most vulnerable industries in the value chain, such as apparel and textiles, are expected to have consolidated suppliers (McKinsey, 2021). Through information sharing, co-development, and organizational coordination, companies can gain complementary synergies that are difficult to accumulate alone, enhance the value of their own resources, gain a relative positional advantage, and enjoy improved performance (Dyer & Singh 1998; Seyoum, 2020; McKinsey, 2021). Further, agile supply chains arguably enable brands to operate in less predictable multichannel environments (KPMG, 2021). For these reasons, we argue that SCI is a core factor in achieving Branding 4.0 principles and is worth further exploration.

Although the literature addresses each of the above three concepts separately, mainly regarding their roles in achieving production flexibility, less is known about the conjoint use of these resources in the Branding 4.0 context. According to resource orchestration theory, companies need to orchestrate resources and managerial acumen to achieve potential advantages and thus superior performance (Chirico et al., 2011; Chadwick et al., 2015; Liu et al., 2016). In other words, performance outcomes seem to be determined by the joint effect of combining resources (Zaefarian et al., 2013; Liu et al., 2016). Accordingly, what we need to know is not only the individual impacts of ML, modularity, and SCI but also how their alignment helps brands successfully transition to a Branding 4.0 approach. To address those knowledge gaps, this study asks an important question: How can modularity, SCI, and ML be used together to offer personalization to customers while maintaining brand identities?

To answer that, this paper reports the findings from 15 in-depth interviews with managers and decision makers from leading brands in China's clothing and footwear industries. Some of the companies are in the Fortune Global 500. We chose companies in China's clothing and footwear industries as the unit of analysis because many of them have already applied modularity in production and adopted advanced technologies such as ML, automation, and robotics. In answering the research question, this paper makes several contributions. Theoretically, this study advances the Branding 4.0 concept in the business-to-business (B2B) context by unfolding, through a resource orchestration lens, a new strategy to support brands in gaining Branding 4.0 competencies. By drawing on the overlapping advantages and contradictory effects of the three resources, this research suggests a "two-tier response strategy" emphasizing the prioritization and hierarchy of resources to reduce the challenges of Branding 4.0 implementation. Our findings have implications for decision makers and managers seeking to understand the Branding 4.0 core principles and goals, and they clarify the importance of ML, modular management, and SCI in optimizing manufacturing, management, and marketing functions for superior brand performance.

This paper is organized as follows. Our investigation begins with a literature review explaining the current knowledge limits and defining the constructs being studied. We then explain the methodology applied and the data collected. The data analysis is then presented, followed by the findings and discussion. The paper concludes with implications, limitations, and directions for future research.

2. Literature review

2.1. Branding 4.0

Branding 4.0 has ushered in a new generation of branding. Branding 1.0 required managers to look at building brand names by focusing on creating iconic products and services that differentiated them from competing brands. Branding 2.0 involved building and maintaining a consistent brand image (Isarabhakdee, 2016), while Branding 3.0 focused on building a social image by addressing societal needs through international frameworks such as corporate social responsibility and corporate shared value (Daye, 2020). Branding 4.0 introduces the era of hyper-customized experiences (Hedden, 2018; Wallace, 2018; Daye, 2020), which make consumers feel unique and serve their needs for belonging, esteem, and self-fulfillment (Hedden, 2018; Wallace, 2018, Santos et al., 2021). Brands joining this fourth revolution become closer to their customers and are more dynamic (Santos et al., 2021, Daye, 2020).

Under the Branding 4.0 paradigm, brands respond to the myriad of customer desires through personalization while keeping their core visual mnemonics' authentic elements consistent

(Wallace, 2018). Isarabhakdee (2016) proposed that Branding 4.0 essentially refers to the collaboration between the brand and its customers through co-creation, either by allowing customers to design their own products, thus enhancing customer engagement and offering customers convenience (Daye, 2020), or by letting them design their own version of the on-brand message (Wallace, 2018). When this happens, however, brands need to give customers tools that are still confined to the brand message's original articulations. That is, to maintain consistency in brand identity, customers can mix numerous variables to make personalized products while keeping the unique combinations "on-brand."

Table 1 captures the current understanding of Branding 4.0 in the existing (gray) literature and the results this era can offer brands. Overall, that limited body of work appears to suggest that Branding 4.0 allows personalization and diversification to be developed and delivered to address individual customer needs. It further argues that brands that successfully manage that process can achieve greater profitability (Isarabhakdee, 2016). However, the literature remains abstract and lacks empirical evidence regarding the Branding 4.0 concept. Although some researchers suggest that Branding 4.0 is beneficial for brand performance, including in profitability terms (Isarabhakdee, 2016; Wallace, 2018), they do not provide a managerial view of how it can be implemented in practice, nor do they attempt to operationalize this highly abstract concept into more accessible dimensions. To address this shortcoming, this paper draws upon the ML, modularity (mainly in product and process), and SCI literature to propose those resources as main methods and innovations through which a firm can develop personalization capabilities (Tu et al., 2004; Wang et al., 2014; Liu et al., 2016; Sharp et al., 2018) within the Branding 4.0 paradigm.

Table 1. Representative studies of Branding 4.0—concept, outcomes, and data sources

No.	Concept of Branding 4.0	Outcomes of Branding 4.0	Sources
1	A brand collaborating with its customers and succeeding together. A shift in the relationship from "dominance–acceptance" to "mutually beneficial cooperation" between brands and customers.	Sustainable development, long-term competitiveness, customer loyalty, and higher profits.	Isarabhakdee (2016)
2	A brand providing individual customers with a personalized service and experience while focusing on using brand elements and maintaining its image.	Reputation, loyal customers, and growing brand value.	Hedden (2018)
3	A brand focusing on individual customers and conveying personalized brand messages to each. Customers can create their own products, while brand designers focus on how brand elements are used and conveyed.	Customers' willingness to work with them in the long run, with potentially higher profits resulting.	Wallace (2018)
4	A brand paying attention to market demand and customers' personal needs while maintaining consistent brand communications to achieve sharper brand focus and recognition.	Higher market share and customer satisfaction.	Daye (2020)

2.2. Machine learning

ML is an evolving field of computational algorithms that can analyze and transform heterogeneous data into knowledge (Lu et al., 2018). Learning through data or experience enables these algorithms to alter or adapt their architecture automatically to achieve the desired results (Sharp et al., 2020). From new or unseen data, these algorithms can constantly optimize their configurations to approach the desired outcomes (El Naqa & Murphy, 2015). These ML features offer inductive, deductive and transductive learning based on inferences made from specific tasks. This could be classified into four types of learning: *supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning*. *Supervised learning* is used to estimate an unknown mapping from known samples, where the output is labeled (Athey, 2018). It helps customer retention via prediction and forecasting; the deep learning system can accurately classify observations from massive images and videos available on the internet (Jordan & Mitchell, 2015). *Unsupervised learning* is based on clusters of observations that may be similar in terms of covariates (El Naqa & Murphy, 2015; Athey, 2018). Such learning can be used to categorize comments and videos or to create outcome variables (Athey, 2018), thus allowing elicitation through dimensionality reduction and the use of clustering techniques to allow target marketing and customer segmentation. *Semi-supervised learning* uses labeled data to make inferences regarding the unlabeled data (El Naqa & Murphy, 2015). *Reinforced learning* provides an indication of whether an action is correct and thus indicates whether the output is correct for a given input (Jordan & Mitchell, 2015). It enables navigation based on robotics with skill-based learning for real-time decisions to be made by managers.

ML-based techniques have been applied to fields beyond marketing such as health care and spacecraft engineering (Jordan & Mitchell, 2015; El Naqa & Murphy, 2015). For industries dealing with data-intensive issues, ML can support the diagnosis of system faults then obtain and present solutions for managers (Sharp et al., 2018). Managers simultaneously use ML to maintain scheduling, manage system diagnostic and prognostic knowledge, and extend equipment life spans (Sharp et al., 2018; Shin et al., 2017). ML can also improve success probabilities for projects underlying a complex situation by fine-turning calculations and providing reasonable solutions and arrangements (West et al., 2018). Managers use these processes for prediction, classification, and clustering or grouping of tasks for predicting outputs (Lu & Asghar, 2020).

In marketing, collecting big data through advanced technology such as ML enables managers to understand individual consumer's requirements and preferences more accurately, thus supporting the provision of personalized advice and products (Wallace, 2018; Jordan & Mitchell, 2015). By improving marketing managers' analyses and predictions, real-time information and knowledge acquired through different ML types consequently optimize their decisions (Sharp et al., 2018). That is even more relevant in product personalization, especially in a changing environment where the proper deployment of products may be a key factor in achieving competitive advantage. Offering personalized experiences and co-creation activities allows brand managers to create a competitive brand positioning and is an important requirement for implementing the Branding 4.0 philosophy (Isarabhakdee, 2016). Hence, we pose that ML is a core resource in the Branding 4.0 nexus.

2.3. Modularity

Modularity refers to dividing a complex system into smaller modules to examine them separately (Tu et al., 2004). Systems with higher degrees of modularity can be disaggregated and recombined into configurations with little loss of functionality (Schilling & Steensma, 2001; Tu et al., 2004). Modularity also enables implementation of large-scale customization (Tu et al., 2004; Wang et al., 2014; Sturgeon 2002; Fixson & Park, 2008; Seyoum, 2020). Research suggests that modularity can increase firms' strategic flexibility, thus enabling them to reorganize manufacturing processes quickly in response to customer requirements and to add product variety without production volume and cost sacrifices (Worren et al., 2002; Tu et al., 2004). Product modularity and process modularity are viewed as two important types of modularity for managing product design and production processes (Worren, 2002; Campagnolo & Camuffo, 2010; Wang et al., 2014). Product modularity can increase product variety through reconfiguration, while process modularity can increase a firm's manufacturing flexibility through resequencing and postponement (Wang et al., 2014)

Product modularity refers to the practices of standardizing product modules so that they can be reassembled/rearranged into different functional forms or shared across crossed product lines. Changing one part does not necessarily require changing others (Ulrich, 1995; Sanchez, 2000; Tu et al., 2004). Companies can provide high product variety at high speeds by using six types of modularization: 1) component-sharing modularity (using common components to design a new product); 2) cut-to-fit modularity (altering the components according to the customer-specified physical dimensions); 3) bus modularity (adding components to an existing series); 4) component-swapping modularity (switching components on a standard product); 5) mix modularity (combining standard components until individual components lose their unique identity); 6) sectional modularity (arranging standard modules in a unique pattern to achieve a different product shape). Product modularity can be used to design diversified end products to satisfy customer needs (Duray et al., 2000; Yan et al., 2019).

Process modularity separates the manufacturing process into standardized modules which can be easily resequenced into new processes in response to changing product feature requirements (Feitzinger & Lee, 1997, Wang et al., 2014). Process modularity has the following features: 1) production processes can be adjusted by adding new process modules; 2) production process modules can be adjusted for changing production needs; 3) processes are divided into standard subprocesses that generate customized units; 4) production process modules can be rearranged so that customization subprocesses occur last (Wang et al., 2014). Tu et al. (2004) proposed that process modularity is also based on the principle of process postponement, i.e., postponing customization subprocesses until a customer order is received or placing those subprocesses in the distribution center. Process modularity enables workstations and conveyor units to be added, removed, or rearranged to create different process capabilities (Cooper, 1999). Process modularity can be used to reengineer entire supply chains to enhance customization, while process postponement enables processes to achieve maximum flexibility (Tu et al., 2004).

Overall, the above literature review indicates that modularity studies focus on the implications of modularity for production processes and product design and its role in achieving flexibility, i.e., increasing product variety while shortening production times. From a consumer perspective, modular products are easier for customers to customize, upgrade, and repair (Tu et al., 2004), thus modularity may support customers' serviceability perceptions when shopping. Modular division, such as dividing products into standard and personalized modules (Duray et al., 2000), may enable a brand to provide personalized options while leaving room for brand elements to be expressed. This indicates that modularity is a potential source of increasing strategic flexibility to enable achievement of Branding 4.0 goals. In this context, this study attempts to integrate modularity into the Branding 4.0 nexus to explore its implications in the context of web interface settings and product design.

2.4. Supply chain integration

SCI is a firm's coordination and synchronization of its supply partners (Liu et al., 2016). It is associated with the complementarity and coherency of activities in the chain (Simatupang et al., 2002; Flynn et al., 2010). Therefore, it requires a firm to collaborate strategically with its partners while balancing its own structure and strategy with those of its supply chain partners (Liu et al., 2016). To create collaborative efforts, firms can engage in four integration activities: 1) information integration (sharing information about various supply chain activities with channel partners); 2) synchronized planning (collaborating with channel partners in planning and scheduling); 3) operational coordination (streamlining its supply chain processes with channel partners); 4) strategic partnership (establishing long-term relationships with channel partners to deploy its resources collaboratively with its channel partners) (Liu e al., 2016).

It has been argued that firms with well-integrated supply chain members can reduce production costs and lead times, increase the speed of product introduction in response to changing markets, enhance production flexibility for a large variety of products, improve product quality, and achieve superior brand performance (Seyoum, 2020). Through in-depth knowledge transfer, a firm can access partners' know-how and learn to improve their product development and production processes, thus reducing product development and cycle times while improving product quality (Seyoum, 2020). Through high information integration, firms can also obtain experience from partners which helps them reduce mistakes and waste to achieve optimal production costs (Tummala et al., 2008; Liu et al., 2016). Trust between partners encourages innovation. Sharing joint responsibility with supply partners also reduces production times and improves production flexibility. This results in improved responsiveness to changing market needs and enhances product availability to address customer requirements (Simatupang et al., 2002). SCI support is therefore claimed to improve firm performance (Flynn et al., 2010).

The above literature defines SCI and the activities needed for collaborative efforts. The existing literature (see Table 2 for a summary) also indicates that SCI, in isolation, brings production speed, flexibility, and production quality benefits. However, hardly any literature discusses the Branding 4.0 effects of SCI in relation to technical innovation and managerial means. The aim of this research is to investigate the role of SCI in collaboration with managerial means and technical innovations, especially modularity and ML, in achieving Branding 4.0 goals.

Table 2. Representative studies on machine learning, modularity, and supply chain integration

	Author(s), Year	Definition	Research context	Study objectives	Research gap / theoretical contributions	Major findings
Machine learning	Bajic et al. (2018)	A subdimension of artificial intelligence, ML is a collection of algorithms which "learn directly from the examples, data, and experience and are able to figure out how to perform important tasks by generalizing from them." (p. 29)	Manufacturing in Industry 4.0	"The objective lays behind the utilization of big data in order to accomplish cost-efficient, fault-free, and optimal quality manufacturing process." (p. 30)	- A preliminary literature review of ML techniques as a part of intelligent systems, the most used algorithms, as well as their advantages and disadvantages within Industry 4.0. - Analyzed the differences between ML and statistics. - Detailed the application, challenges, and future trends of ML.	- ML extracts knowledge from big data to achieve defect-free and fault-free processes. - ML algorithms have uses in optimization, control, troubleshooting, security, and verification, which are all further beneficial for cost reduction without affecting production quality.
	Sharp et al. (2018)	ML is "a subset of artificial intelligence that focuses on autonomous computer knowledge gain." (p. 170)	Smart manufacturing, Industry 4.0	- A literature review investigating areas where ML can play a vital role; - To optimize firms' schemes and applications of ML in production cycles.	A literature survey on ML in multidisciplinary, cross-domain focus areas, highlighting the current gaps in ML applications in manufacturing.	The results indicates that ML plays a vital role in knowledge management, decision support, data management, and life cycle management. However, the study also suggests that to achieve more flexible, lean, and energy-efficient manufacturing, firms should not only apply ML but also integrate it with other resources such as human resources, automation and data, and the industrial internet of things.
Modularity	Duray et al. (2000)	"A relative property with products characterized as more or less modular in design." (p. 609)	Mass customization	To assess whether mass customization is a robust concept applicable across a range of industries.	- Developed a conceptual model of mass customization to identify and classify mass customizers. - The research explored different approaches to mass customization and compared impacts of each approach on brand performance.	A firm's performance is better when they use standard modules and employ modularity in the production cycle assembly stage.
	Tu et al. (2004)	Modularity refers to "the degree to which a system's components can be separated and recombined" (p. 150). Modularity-based manufacturing refers to "the use of modular principles to create components and processes that can be configured into a wide range of end products to meet specific customer needs." (p. 147)	Mass customization	To investigate the relationship between modularity-based manufacturing practices and mass customization to identify a good strategy for improving a firm's mass customization ability.	- Defined modularity-based manufacturing practices and developed an instrument to measure it. - Proposed a theoretical model of the relationships among customer closeness, modularity-based manufacturing practices, and mass customization.	- Modularity-based manufacturing practices and its subdimensions (including product modularity, process modularity, and dynamic teams) have a positive impact on mass customization. - Customer closeness has a positive impact on mass customization - Customer closeness positively impacts modularity-based manufacturing practices, which in turn positively impact mass customization.

	Jacob et al. (2011)	Modularity represents a hierarchically nested system where product modularity is defined as “the use of standardized and interchangeable architectural elements that enable the configuration of a wide variety of end products” (p. 125). Process modularity is defined as “the incorporation of adaptable and reconfigurable tooling and routings into production operations to meet heterogeneous demand effectively.” (p. 126)	Manufacturing	“To build on general modular systems theory by examining empirically the effects of both product and process modularity on intermediate and final performance outcomes.” (p. 123)	Empirical evidence on the impact of product modularity on a firm’s manufacturing and performance; provides a theoretical basis for modularity-based manufacturing strategies.	Product modularity is key in modular systems, which in turn facilitate process modularity, and enhances manufacturing agility, improves growth performance, and increases market share.
Supply chain integration	Flynn et al. (2010)	“The degree to which a firm strategically collaborates with its supply chain partners and collaboratively manages intra- and interorganization processes.” (p. 59)	Operations management and Performance	To examine the relationships between SCI and both operational and business performance.	Expands the dimensions of SCI and adds to the literature on the interaction of these dimensions and their impact on firm operations and business performance.	The three dimensions of SCI (i.e., internal integration, customer integration, and supplier integration) are directly and indirectly related to operational performance, within which internal integration is also directly related to business performance.
	Liu et al. (2016)	“The degree to which a firm collaboratively deploys its resources and capacities with channel partners.” (p. 14)	Operations management and performance	“To investigate how organizations can deploy IT [information technology] competency in a manner that is conducive to materializing the benefits of SCI.” (p. 13)	Theorized how IT and SCI interact to affect firm performance.	Firms with high SCI achieve higher performance than firms at other levels. The interaction between SCI and IT had an impact on higher performance, while firms with different SCI levels need to align with different IT capabilities to gain those impacts.
	Seyoum (2020)	The practices of a firm to collaborate strategically with upstream and downstream suppliers.	Manufacturing in China’s auto industry	To investigate the relationship between modularity and performance to identify good strategies for increasing performance.	Theorized the relationship among product modularization, SCI, firm’s relative location advantage and firm performance, the mediating effects of SCI, and firm relative positional advantage in the relationship between product modularity and firm performance.	The mediating effects of SCI and firm relative positional advantage in the relationship between product modularity and firm performance may have implications for using modularity as an important framework for studying the strategy of global auto firms in China in their attempts to create dynamic capabilities.

2.5. Machine learning, modularity, and supply chain integration for Branding 4.0

Current changes in customers' customization and diversification needs, coupled with uncertainty in upstream and downstream client demands, indicate the dawn of a new era of branding requiring practices allowing customer preference-based changes to product design during the manufacturing process. In theory, such customization would lead to increased production costs and times, thus increasing customers' sacrifices, such as delivery times and price premiums, to obtain personalized products. Therefore, the use of managerial means and technical innovations to control processes with shorter response times and increased flexibility becomes important for coping with Branding 4.0.

ML, modularity, and SCI have each been proposed as enablers for future brand development and production flexibility. However, the integrated effect of these three organizational innovations on future brand development remains a topic of immediate interest. This is supported by the tenets of resource orchestration theory, according to which companies need to orchestrate resources and managerial acumen to realize potential advantages and thus superior performance (Chirico et al., 2011; Chadwick et al., 2015; Liu et al., 2016). This suggests that performance outcomes could be better achieved by the joint effect resulting from the combination of resources (Zaefarian et al., 2013; Liu et al., 2016). Accordingly, we need to know not only the respective impacts of ML, modularity, or SCI on brand performance but also how alignment of these resources helps brands to transition successfully to a Branding 4.0 approach. To achieve that understanding, this paper investigates the Branding 4.0 concept, antecedents, and consequences in the context of China's garment and footwear industries. It reports the findings from 15 in-depth interviews with managers and decision makers of leading brands, including some Fortune Global 500 companies.

3. Methodology

3.1. Research design

Given the novelty and topicality of our research area, a qualitative approach was deemed suitable for guiding this study. Exploratory research conducted under the qualitative paradigm provides researchers with a flexible design allowing findings to "unfold, cascade, and emerge" (Lincoln and Guba, 1986, p. 210), which makes the approach particularly beneficial to newly emerging topics such as Branding 4.0. Specifically, we conducted in-depth, semi-structured interviews with 15 brand managers and decision makers. This approach allowed us to gain a thorough understanding of the participants' perspectives on Branding 4.0, which is a topic more geared toward discovery and exploration (Chenail, 2011). The interviews centered on four discussion areas arising from the literature review—Branding 4.0, ML, modularity, and SCI (see Table 4)—to enable deep insights and probes. Ethical approval to conduct this research was obtained from the lead author's institution prior to the data collection.

3.2. Research context and sampling

Many companies in China's clothing and footwear industries have become famous using smart manufacturing solutions by combining marketing with cutting edge technological tools, such as ML and robotics, and managerial means such as modularity and SCI. These efforts have allowed their customers to become architects of their personalized choices through personalization programs enabling bespoke design, thereby applying customer individuality and self-expression through product customization processes. Customers can create their own products by selecting and combining predefined options and/or uploading their own texts and pictures. Large-scale production and customer demand for customization made companies in China an appropriate unit of analysis for this research because their practices match this study's objectives and questions, thus they offer an opportunity to address the current knowledge gap and contribute to the academic literature (Qi et al., 2009). Through investigating these brands, we may better understand their strategies and the efforts required to transition toward a fully personalized product offering. Studying brand–supplier relationships may also shed some light on the ecosystem they inhabit and how it affects their achievement of Branding 4.0 goals.

Given our focus on China's clothing and footwear industries, we used random sampling of the research population of interest (i.e., members of China's Garment Industry Association) to recruit participants. Specifically, the study's lead author contacted the head of the China's Garment Industry Association and explained the research interview intentions, procedures, and guidelines. Based on the explanation provided, the researcher was granted access to the database of garment enterprises. The database contains a total of 303 emerging brands, and the researchers spent a week contacting them one by one to explain the interview intentions and procedures. In total, 15 managers agreed to participate. The interviewee list included representatives of several leading enterprises, including Fortune Global 500 and Top 20 Costume in China brands, and small and medium-sized enterprises honored as "The Highly Influential Emerging Designer Brands." These companies operate both in the B2B (providing end products, components, or materials to other companies) and business-to-consumer (B2C) markets. All interviewees held brand senior management team positions such as CEO, president, general manager, marketing manager, and supply chain leader. To preserve their anonymity, brand and interviewee names are kept confidential. Table 3 provides a summary of the participant profiles.

Table 3. Participant profiles

Contributors	Affiliation	Job role	Relevant work experience (years)
C1	E-commerce department	E-marketing manager	7
C2	Operations department	Supply chain manager	7
C3	Supply chain center	Supply chain manager	10
C4	Entrepreneurship	Vice president	15
C5	Operations department	Executive deputy general manager	10
C6	Marketing department	Marketing manager	7
C7	Supply chain center	Supply chain manager	8
C8	Operations department	General manager	11
C9	E-commerce department	Marketing manager	9
C10	Operations department	General manager	10
C11	Operations department	Supply chain manager	9
C12	Marketing department	Marketing manager	10
C13	Entrepreneurship	Vice president	12

C14	Entrepreneurship	Acting vice president	8
C15	Operations department	General manager	13

3.3. Semi-structured interviews

We constructed the interview questions around the abovementioned themes of interest emerging from our literature review (see Table 4). Interviews started with some "grand-tour questions" (Creswell, 2012) regarding their personal details, positions, and years worked with their brands. The questions then explored the participants' understanding of the Branding 4.0 concept, management, antecedents, and possible outcomes. All interviews were conducted face to face in the participants' offices using Mandarin, which is the participants' native tongue, to make them more comfortable expressing their views and insights. Interviews lasted from 30 minutes to 90 minutes. Table 4 lists sample questions asked during the interviews, which were first transcribed verbatim in Mandarin then translated into English for thematic analysis by the researchers. The reliability of the translations was checked by sharing them with two PhD scholars and three academics with knowledge of both languages who worked in the same field at different universities.

Table 4. Interview questions

Category	Scheduled questions	Probes	Reference for question development
Branding 4.0	**- What is Branding 4.0, from your perspective?** **- Was there a difference in your brand performance after implementation of Branding 4.0 principles using different methods?**	- The concepts of Branding 4.0 - The importance of and advantages that a brand achieves from adopting Branding 4.0	Isarabhakdee (2016); Hedden (2018); Wallace (2018); Daye (2020)
Machine learning	**What was the role of ML in the implementation of Branding 4.0 principles?**	- Have you used ML for implementation of Branding 4.0 principles? (If yes/no, why?) - How is ML employed for the implementation of Branding 4.0? - Is there a further plan to further adopt ML in pushing Branding 4.0? (If yes, can you describe the plan? If not, why?)	Sharp (2018); West et al. (2018); Lu & Asghar (2020); Jordan & Mitchell (2015); Shin et al. (2018) Giglio et al. (2020)
Modularity	**What was the role of modularity in the implementation of Branding 4.0 principles?**	- Has product modularity helped in pushing Branding 4.0? (If yes, how?) - Has process modularity helped in pushing Branding 4.0? (If yes, how?) - Has modularity applied at other levels helped in pushing Branding 4.0? (If yes, can you detail which levels and how it helped?) - Have you encountered any struggles when using modularity at any levels? (If yes, can you provide details? How did you solve the problem?)	Duray et al. (2000); Tu et al. (2004); Jacob et al. (2011); Wang et al. (2014)

Supply chain integration	**What was the role of SCI in pushing Branding 4.0?**	- How would you describe the role of SCI in implementation of Branding 4.0 principles? - Are there activities your brand applies for supply chain integration in terms of Branding 4.0? (If yes, can you detail them?) - Have you encountered any struggles during the process of SCI? (If yes, can you detail them? How did you solve the problem?)	Seyoum (2020); Tummala et al. (2008); Liu et al. (20160; Simatupang et al. (2002); Flynn et al. (2010)

3.4. Data analysis

The purpose of this paper is to discover inductively the meaning and outcomes of Branding 4.0, and the role of ML, modularity, and SCI in managing it. We adopted the Glaser and Strauss (1967) grounded theory approach as the technique of analysis and carried out "open coding," "axial coding," and "selective coding" of the 15 interview transcripts in turn. The analysis followed a step-by-step procedure to ensure rigor (Gioia et al., 2013). Initial manual coding and recoding in NVivo was undertaken by two researchers, who read and examined the data, identified the related categories, and conceptualized them. Categories were labeled, then the category attributes and dimensions determined. The researchers subsequently connected categories using "axial coding" to discover and establish the relationships. "Selective coding" followed to extract a "core category" through integration and condensation of all the previous categories. Table 5 summarizes the complete data analysis process the researchers followed.

Table 5. Data analysis process

Step 1	Researchers with bilingual skills (i.e., English and Mandarin) conducted interviews in the local language and later transcribed them into English so that not only words but also observations made during interviews were captured in the data for analysis purposes.
Step 2	Two researchers conducted an initial manual analysis using open coding techniques for a preliminarily verification that the interview data were consistent with the topics of interest.
Step 3	The two researchers explored their individual interpretations before reaching a consensus through analyzing Branding 4.0 coping methods. This led to the development of the analytical triangle used as the initial guide for subsequent data analysis.
Step 4	After the initial manual analysis, the research team imported transcripts into NVivo to further develop codes based on interview quotes.
Step 5	The researchers went back and forth between first-order (associated quotes from interviewees) and second-order (theory-centric) categories. Figures 1 and 2 provide detailed evidence of this process.
Step 6	The research team then improved the triangle based on intertwined movements to show how the themes interrelated. Figure 3 illustrates the process.

4. Findings

The respondents were aware that providing a personalization experience while conveying brand identity to individual customers is the core object of Branding 4.0. That is probably because fashion industry brands face a competitive market and the interviewees are very forward-thinking and far-sighted managers.

> *The 4.0 era is an inevitable trend of development, and in China, we call 4.0 "Made in China 2025." Looking at home and abroad, including Australia, the UK, and the United States, for example, for a brand to obtain advantage in the new era, it must capture the needs and mentality of customers, even for well-known brands such as Nike. If a brand adheres to the traditional approach, the brand's profits will become thinner and thinner, because the brand and their competitors have not formed a differentiation, which is when our brand can accomplish a task, and our competitors can also accomplish it. In this way, we will not be competitive. And if we stick to the tradition, we won't be able to make a profit if something unexpected happens. In order to seek long-term development, our brand has received more orders and turned to focus on customization services for the audiences, and we opened an online platform to interact with customers.* (C5)

Co-creation processes and bespoke products are both important Branding 4.0 components. The above quote confirms Wallace's (2018) claim that brands which engage customers in product co-creation activities and customization enjoy stronger competitive advantages and customer loyalty. The brand's role is to predefine the modules that customers can use in the product form and that they retain brand elements, thus ensuring that both co-created activities and final products are personalized expressions of the brand identity. Brands should focus on ease of use and interaction enjoyment while ensuring the timely deployment and quality of goods.

> *Branding is human-centered. The goal of personalized programs is your [customer] brand recognition. In addition to bringing you affordable products, we consider your emotional and even spiritual needs. In fact, when you join the design, to identify your own product, you engage your emotions. When you also approve the final customized product that we delivered, compared to other brands, you will be more identified with us. You will feel more attuned to our brand so will remember our brand.* (C13)

In discussing their views on Branding 4.0, interviewees described the main management strategies linked to achieving Branding 4.0 objectives. To cope in the new era, decision makers and managers alike activate technical and managerial innovation including but not limited to ML, modularity, and SCI to enhance their personalization capabilities. Informed by the analytical framework (see Figure 3 for an updated version), the following sections present our findings on these three core resources as a multilayered strategy in Branding 4.0. Figure 1 summarizes those findings.

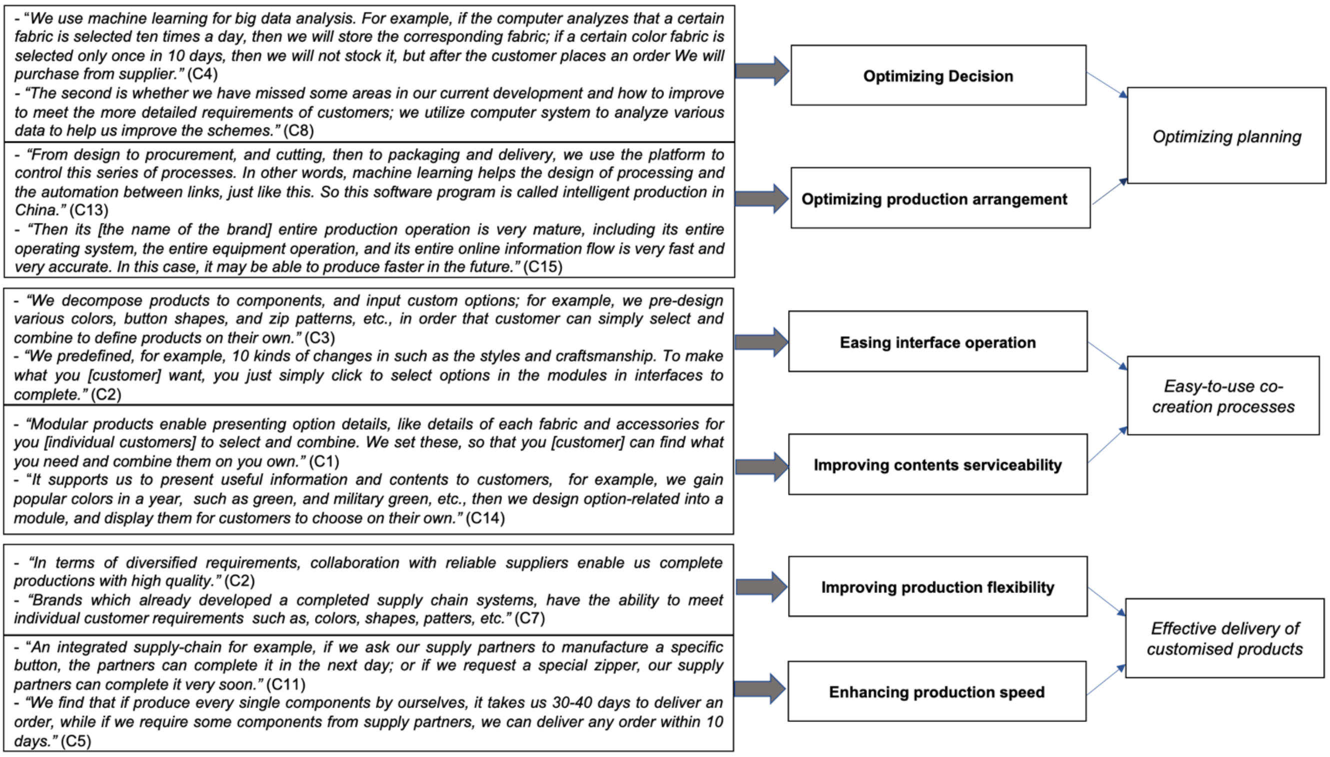

Figure 1. Machine learning, modularity, and supply chain integration as Branding 4.0-supporting dimensions: data and themes

4.1. Machine learning and Branding 4.0

While previous literature and anecdotes note the superiority of ML in large-scale data storage and administration (Sharp, 2018), our interviewees revealed that ML, through its capacity to analyze big heterogeneous data across a brand's lifetime, helps decision-making in two areas: optimizing solutions and optimal scheduling of equipment on production lines.

> *The production for garments involves designing, purchasing, cutting, and sewing, then packaging and delivery. We use machine learning algorithms and other software to control and optimize the process, which is to use it to optimize the time and control the automatic processing between links; this is it. So, it is related to the application of software. In China, we call it intelligent production.* (C4)

For Branding 4.0, company presidents, CEOs, and general managers are mainly concerned with development goals and formulating related strategies. In our case, the interviewees noted that using ML-based computer systems to analyze complex data enables them to obtain more optimized solutions. For example, decision makers mentioned obtaining investment returns more quickly and getting optimized cost estimates and schemes. They also reported extending the ML system to all work units to optimize plan formulation and execution effects in each.

4.2. Modularity and Branding 4.0

Our interviewees confirmed that both product modularity and process modularity are important in improving flexibility in terms of producing a large variety of products (Tu et al., 2004; Wang et al., 2014). Furthermore, the marketing managers reported adopting modularity practices to optimize online customer interaction interfaces. For instance, the options provided to customers are included in the modules for them to define their own products by selecting and combining the options displayed on the interface. That modularity is applied to online co-creation activities may be related to modular products being easier for customers to customize and update, with resulting greater usability and maintainability.

> *Similar to the application of modules in product design, in the web interface design, we also disassemble the product into components, and input options in components for customers to choose and combine for their own products. For example, in the button module, we set different submodules such as button style and button color, and each submodule includes a variety of options. Customers can define their own products by clicking on the content in different modules.* (C1)

Marketing managers are primarily responsible for brand–customer interactions, especially co-created activities, for Branding 4.0. In the co-creation process, customer participation and customer enjoyment affect customer experience (Lee & Chang, 2011; Aichner & Coletti, 2013). Marketing managers attempt to enhance the attractiveness of the co-creation process so that individual customers can perceive good personalization-related experiences.

> *We also make adjustments frequently. For example, when a customer proposes a new requirement, we need to make adjustments to meet their needs as much as possible... If it [the options customers expect] is not currently in the present options, the customer can give us feedback on what they need, we set intelligent customer service and human customer service personnel to communicate with them. At present, it takes us some time to respond to the demands and make corresponding adjustments in the interface, as we need to conduct systematic analysis and evaluation then make adjustments.* (C6)

However, customer preferences and habits are constantly changing (Miceli et. al., 2013), including the perceptions of the ease of use of modular interfaces and the usefulness of the options offered by modules. This may in turn reduce the perceived enjoyment of co-creation activities. Our interviewees pointed out that resolving this conflict requires an ability to understand each customer's preferences quickly and accurately.

4.3. Supply chain management and Branding 4.0

While respondents agree that product and process modularity can improve the efficiency of manufacturing diversified products, they also point out that relying on modularity practices to improve production efficiency is far from enough. In our case, supply chain managers emphasized the role of collaborative efforts in improving production flexibility and efficiency. They also mentioned that cooperation with suitable suppliers can reduce the inventory pressure and production cost.

> *We need to integrate the original design link, online platform, and ERP [enterprise resource planning]. This will simplify work procedures, reduce work difficulty, and then increase production speed and save production costs. For personalized production, if there is no well-controlled production cycle, the final customer will have a long waiting time. For example, for personalized production, we need a variety of different raw materials. It is difficult for us to produce different raw materials in a short period of time. We can only obtain them through suppliers. This is because we need to open the entire supply chain system, and the integrated supply chain should contain reliable suppliers. If the supply chain system is not integrated well, when a customer asks us to customize a piece of clothing, we may not be able to deliver a lot of it. In the end, we were unable to deliver the parts to the customer's order.* (C3)

However, the supply chain managers' responses also reveal the problems that may arise in SCI processes, such as disrupted information flow between brands and supply chain partners or excessively long and complex procedural flows. Such problems in turn affect production efficiency and the ability to cope with changing demands.

> *As I just mentioned, the resource, the resources of the supply chain. It may not be enough. For example, if we need a special kind of button, it may take us a lot of effort to find a suitable supplier which is able to make it. Or if we receive an order that a customer requests green fabric for a T-shirt, while we do not produce green fabrics, and we could not contact a reliable supplier of green fabric within time, our delivery will face problems. Another point, such as it [the factory] did not arrange the lead time well. For example, if there is a factory we cooperate with, their production order schedule is already full, but the information between us is not circulated in time, and we don't know that the schedule of this factory is full, and we still send our order to you [the factory] to produce it, this will greatly extend our waiting time. Do you understand what I mean?* (C11)

4.4. The side effects of modularity and supply chain integration for Branding 4.0

While managers implement modularity practices and collaborative approaches to help achieve Branding 4.0 goals, they do not always find these approaches to be helpful. For example, there may be a conflict between using modularity to create user-friendly interfaces and an individual customer's perceptions of ease of operation and content serviceability due to their changing preferences and habits.

> *Modularity is very important for us to be able to process customization. But at present, the personalized services we provide are not yet very precise to individual*

customers. If we can achieve accurate recommendations, that is to say, if we can accurately know the preferences of individuals, then for what you expect to see, the interface can show exactly that to you, this is the most perfect. (C12)

With constantly changing individual consumer demands, untimely information transmission between brands and consumers may result in the designed modules being unable to accommodate fully the customer needs when required. It may even be difficult for brand managers to design and change the modules. Untimely and inaccurate information transmission also affects SCI, with a resulting negative impact on the achievement of Branding 4.0 goals.

Although we always need to cooperate with suppliers, customized business requires us to have better communication with the cooperation factories. For example, a customer has made special requirements on a certain part, but the information has not been circulated to the factory, then it will cause trouble… Or if the delivery date is not coordinated between us, it will also cause trouble. (C2)

Furthermore, disrupted information flow reduces upstream and downstream suppliers' efficiency and accuracy in fulfilling the assigned tasks, thus potentially causing longer lead times. Information disruption also prevents brands from improving their fluency in working with supply partners so that the companies and brands involved in the supply chain, indeed the entire supply chain system, cannot enhance their responsiveness to changes.

Our investment in customization service is constantly expanding because it is in line with trends, and also in line with reality. If a link is out of touch, it will cause delays in delivery or a decline in product quality. As a brand in Shishi (a city in China), we need to coordinate production with cooperative companies, that is, the links between cooperating companies needs to be tight, rather than each co-factory doing itself. Each co-factory needs to be able to complete its tasks independently, but there is a need to develop an overall streamlined step plan from an overall level. (C15)

However, marketing and supply chain managers also reported that decision makers introduce ML systems to their departments and that their use can resolve the above conflicts. The managers also stressed that using ML systems to optimize plans, execution times, and personnel arrangements can help departments to achieve better performance.

4.5. Machine learning in modularity and supply chain integration

Modularity practices and collaboration efforts do not always support a brand's ability to cope with Branding 4.0, but the application of ML at all levels can support the ability to optimize modularity practices and integrate supply chains. Figure 2 illustrates the application of ML algorithms to schedule modularity practices and integrate the supply chain in response to Branding 4.0 challenges.

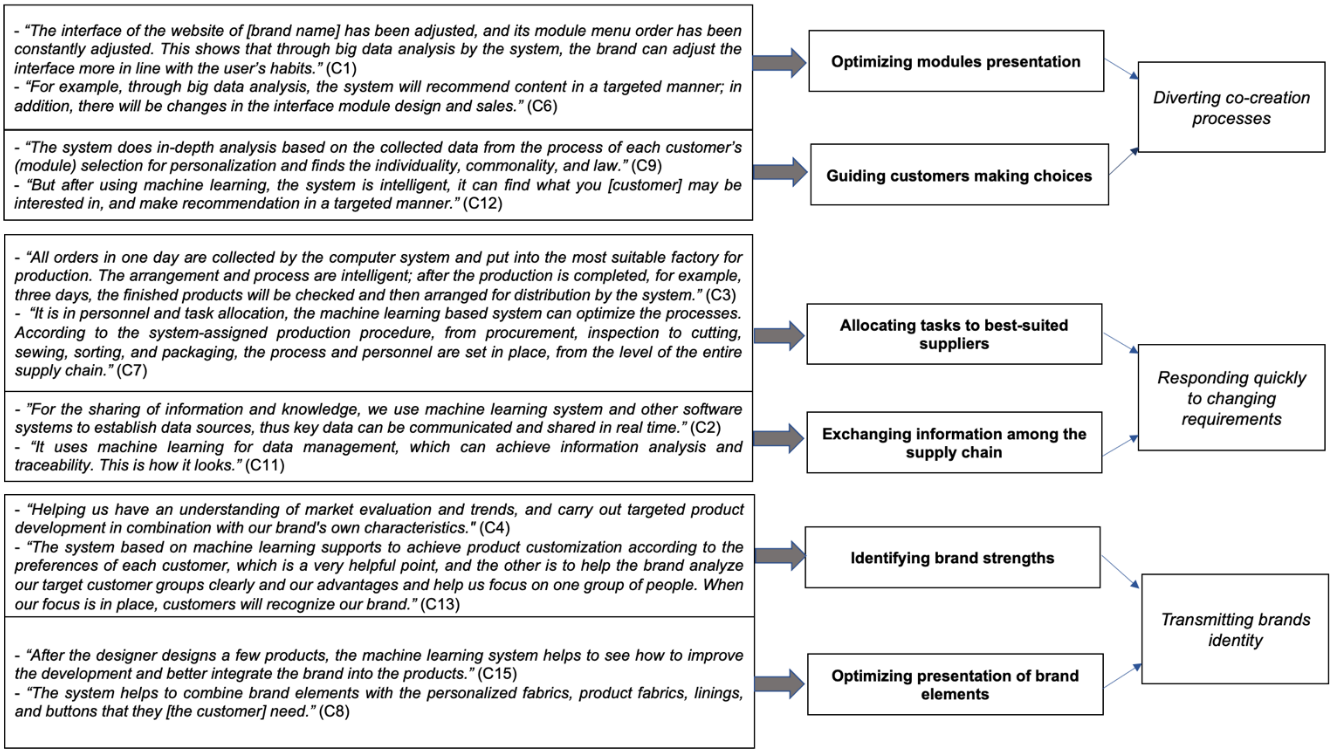

Figure 2. The effect of integrating machine learning in modularity and supply chain integration processes

Our interviewees, especially the marketing managers, claimed that real-time analysis of customer personal data and big data through ML systems can support them in predicting individual customer preferences faster and more precisely. Through the suggestions generated, managers and related specialists can also improve the modular layout and content presentation more effectively. In other words, ML can enable module content and presentation to be more targeted so that individual customers can perceive a more personal co-creation activity and consequently get a better customization-related experience.

> *It analyzes your [customer] personal history, including shopping habits, choices made, etc., to predict your [customer] aesthetics, and it will actively recommend you [customer] styles that match your body and aesthetics; on this basis, you can then choose and combine from various modules, such as detailed decoration and so on.* (C9)

By automatically analyzing real-time data (Sharp, 2018), ML greatly reduces the work intensity for managers and workers. Our interviewees revealed that the quick capture of individual customer preferences using ML optimizes the application of modularity practices in interfaces and production. Optimizing modularity practices, especially in production, can help with the integration of supply chains, including reducing the complexity of steps and waiting times (Sharp, 2018), thus greatly reducing the related work intensity.

Quick responsiveness requires us to have flexible production capacity. Once we can use the machine learning system or other software to help us quickly obtain consumer demands, and then when we receive the consumer order, we save more time to contact the appropriate suppliers and start manufacturing… The more standard the front end is, the faster the subsequent manufacturing will be, the higher the efficiency will be, and the lower the production cost will be. (C1)

The supply chain managers interviewed emphasized the positive impact of integrated supply chains on a brand's ability to respond quickly to changing demands. By using ML-based computer systems to analyze the data, managers can find suitable suppliers faster and the whole process is more streamlined. Moreover, the executives noted that the use of computer systems based on ML algorithms improves the effectiveness of information delivery to related companies, thus contributing to improving the brand's ability to respond quickly to individual needs. The managers also pointed out that using ML systems has significantly reduced the cost, time, and effort invested in making arrangements.

All production systems must be compatible with the presenting production goals; as our production goals are updated, the entire process needs to be reorganized. Using the computer system can help us process the entire production chain and supply chain. (C7)

In Branding 4.0, the goal of a brand is not only to provide a personalized experience to individual customers but also to transfer the brand identity to them so that they can recognize the brand and distinguish it from its competitors. Interviewed decision makers noted that computer systems based on ML algorithms identify brand strengths more accurately through analyzing data on sales, customer feedback, and revenues. Such systems can also make more specific and targeted suggestions on the expression of brand elements to help decision makers successfully convey brand identity to every customer.

That is, the goods are the foundation, whether the goods can be recognized by customers, and whether our brand can be recognized, are the fundamental two points. For example, if you [customer] go to buy a T-shirt from Air Jordan, and the reason that brand can sell goods at that price is because their logo has been well recognized; this is the first point. The important thing is that we have to analyze our own advantages, using machine learning software, and other intelligent software to analyze various data; for instance, the software figures out our advantage lies in the cost-effectiveness, the texture of the product material, and a certain design, which generate customer recognition of our brand and then he [customer] will be more willing to choose our brand, and to engage in personalization-related activities. (C10)

Based on our interview findings, the application of ML algorithms, modularity practices, and SCI helped brands to achieve Branding 4.0 goals in terms of optimal strategic arrangements, brand–customer interactions, and improved production efficiencies. The exploratory research also revealed that the advantages of using ML systems to analyze heterogeneous data can be applied at the decision-making, marketing management, and SCI levels to improve decision makers' and managers' effectiveness in formulating strategies and implementing policies for improving brands' coping abilities. That is to say, the use of ML algorithms can optimize decisions, modularity practice schedules, and SCI directly and indirectly to enhance brand ability to cope with Branding 4.0. Figure 3 captures the interview findings in an analytical triangle.

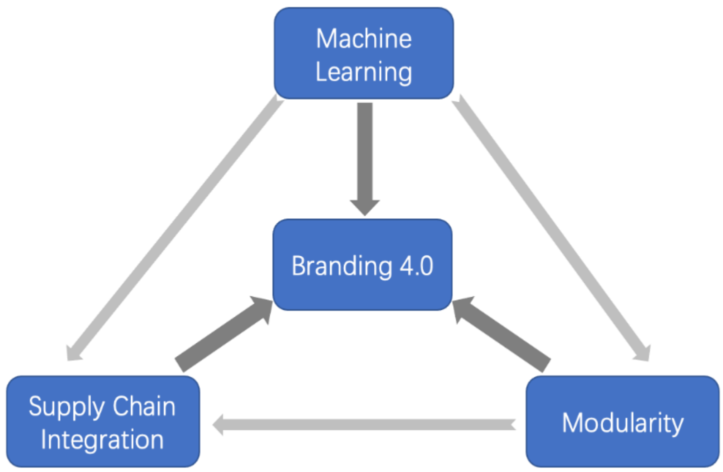

Figure 3. The nexus of Branding 4.0—an analytical triangle

5. Discussion

The findings suggest that the Branding 4.0 concept refers to an assembly of personalization cues offered to customers through which a brand can meet individual desires while maintaining authenticity and consistency of its visual mnemonics (Wallace, 2018). The findings indicate that personalization goes beyond one-to-one communication with customers and providing personalized recommendations based on their preferences to allow them to enjoy co-design activities to co-create products. This is in line with the Wallace (2018) and Santos et al. (2021) findings, as shown in the literature review. Brand capacity to deliver personalized products quickly is another key success factor in this process (Pine, 1993; Tu et al., 2004). Our findings confirm that brands committed to personalization have wider access to customers, better reputation, acquire a loyal customer base (Hedden, 2020), achieve competitive advantages (Santos et al., 2021), enhance their brand identity, and strengthen customers' relationships with the brand. Consequently, these brands will likely obtain higher profitability, as shown by previous studies (Isarabhakdee, 2016). On the other hand, our participants noted that the fourth branding revolution is an ongoing trend posing multiple challenges and requiring inevitable technical-, technological-, and operational-level adjustments, as discussed below.

All the managers stressed that ML, modularity, and SCI are key determinants in achieving Branding 4.0. Specifically, the decision makers and managers relied on a two-tier coping strategy to achieve Branding 4.0 goals. First, ML, modularity, and SCI are considered as three fundamental coping dimensions which optimize efficiency and effectiveness in plan–design–manufacturing. In addition, the application of ML in modular management and supply chain management further optimizes the ability to achieve the goals through data analysis and problem-solving capabilities, including in terms of production and supply delays. Figure 4 illustrates the two-tier response strategy which companies can use to address Branding 4.0 challenges. We propose that strategy as the main contribution of this study.

Previous studies have shown that ML is a knowledge management tool that converts heterogeneous data into useful insight (Sharp, 2018) and is able to both create and transfer knowledge between different applications (Lu et al., 2018). Data from our interviews support this, as our sample decision makers and managers appear to use ML to develop optimal plans and solutions from big data, reach decisions, and improve schedules that help them to achieve the best possible results. ML treats customer information as an entirety and deeply analyzes customer similarities and commonalities before generating knowledge and advice on how a brand can better combine its visual identity elements into personalization strategies. On that basis, by employing ML in the web interface modularity, a brand can communicate with customers one-to-one in real time, as the algorithms are able to analyze individual customer's data, extract their desires, and make personalized recommendations. However, ML's real strength emerges when it is used in conjunction with modularity and SCI, as explained below.

The existing literature depicts modularity in product and process as supporting high-quality, large-scale, and quick delivery of individually customized products (Pine, 1993; Tu et al., 2004; Wang et al., 2014). Our research supports these suggestions and further posits that applying modularity to a web interface improves the ease of use of co-design processes for customers and thus improves the serviceability of brand–customer interactions. Most importantly, our findings highlight ML's critical role in this process. Managers and executives from brands in our sample use ML-provided knowledge to obtain optimal suggestions for quickly modifying the presentation of modules in line with customer changes and their individual demands. By combining modularity with ML, brands can better help customers to select options based on their preferences and visualize the products before making a choice. This maximizes production flexibility and enhances the brand's ability to respond to customers' diversified needs (Tu et al., 2004; Wang et al., 2014).

This research also found SCI to be another critical factor enabling a brand to achieve its Branding 4.0 goals. Strategic SCI leads to the fast and high-quality delivery of diversified requirements. Our study supports the notion that SCI requires a synergistic effort on four levels, i.e., information integration, synchronized planning, operational coordination, and strategic partnership (Liu et al., 2016). Notably, our findings indicate that ML supports the integration of data and information among upstream and downstream suppliers to enable knowledge sharing, which enhances cooperation between enterprises and strategic partnerships. ML also improves the productivity of enterprises along the entire chain, enables suitable supplier–product matching, and offers suggestions that can help in delivering products to the corresponding clients. Those benefits, in turn, enable brands, along with upstream and downstream clients, to work more efficiently and effectively to produce diversified items which meet individual customer's personalization needs and hence the objectives of Branding 4.0.

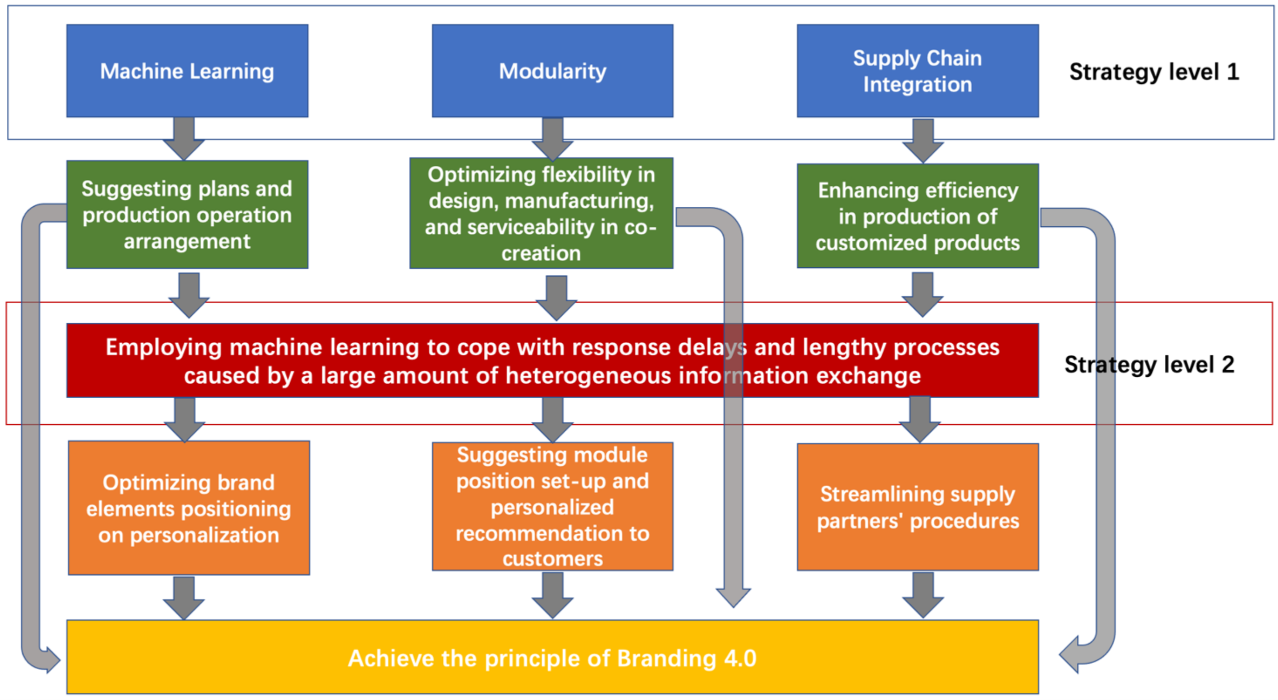

Figure 4. A two-tier response strategy to the objectives and principles of Branding 4.0

6. Conclusion, implications and future research

This study contributes to the industrial marketing literature by investigating the concept of Branding 4.0 from a manufacturing and mass-customization perspective to suggest a two-tier response strategy to Branding 4.0 challenges based on the orchestration of three core resources—ML, modularity, and SCI. Overall, this study found that: 1) ML enables brands to address market demand in a timely fashion through more efficient knowledge management, optimized decision-making, and problem-solving; 2) the use of modular principles not only benefits a firm's manufacturing capability for customized products but also supports serviceability and strengthens customer relationships; and 3) SCI enhances production flexibility and speed while supporting a brand's ability to reduce inventory pressure and production costs. Each finding has direct implications for Branding 4.0 practice and research. Most importantly, the findings highlight the joint effect of these three resources. More specifically, applying ML to modularity and SCI can help brands to cope with delays, both in information and production, and any supply chain conflicts that might otherwise deter them from achieving their Branding 4.0 goals, as illustrated in Figures 3 and 4. Our two-tier response strategy is this study's main contribution, both theoretically and managerially.

Theoretical implications. A nascent literature stream has started to conceptualize the term Branding 4.0 (Isarabhakdee, 2016; Hedden, 2018; Daye, 2020). However, to the best of our knowledge, and as shown in Table 1, the literature remains very vague regarding the meaning and implications of Branding 4.0, with almost no academic work dedicated to the topic. Our research clarifies the emerging concept of Branding 4.0 and provides researchers with a three-dimensional nexus and an analytical framework supported by empirical evidence from managers and decision makers from leading brands. Our framework not only reinforces early conceptual work by Isarabhakdee (2016) and

Daye (2020) but also opens a new avenue of academic research by placing Branding 4.0 on the theoretical map of brand development. Our strongest theoretical contribution stems from the use of scholarly work on mass customization, artificial intelligence, and the supply chain to inform a tripartite framework (see Figure 3) and a two-tier response strategy (see Figure 4) that highlight the joint effect and potential of ML, modularity, and SCI in supporting brands transitioning to Branding 4.0. These two frameworks provide a theoretical basis for: 1) operationalizing Branding 4.0; and 2) using a resource orchestration lens to explore how brands can respond to Branding 4.0 adoption challenges (Chirico et al., 2011; Chadwick et al., 2015). More specifically, our findings show how ML's data analysis, knowledge conversion, and transmission capabilities could benefit both modular management and supply chain tasks to optimize the product co-design process and timely responses to customers' changing demands. These novel findings could pave the way for future interdisciplinary ML application and research beyond the remits of technological fields, i.e., operations management. Furthermore, we contribute to the specific field of mass customization through modularity by showing the latter's advantages beyond supporting flexibility in large-scale manufacturing (Duray et al., 2000; Tu et al., 2004; Jacob et al., 2011). We demonstrate how modularity also benefits customer relationships and perceived brand serviceability, with direct implications for the marketing domain. Finally, by integrating the SCI concept into the Branding 4.0 nexus, we draw marketing scholars' attention to the critical role of downstream and upstream partners in achieving production flexibility and speed for enhanced personalization beyond the more established information sharing, synchronized planning, and operational coordination functions currently addressed in the literature (Liu et al., 2016).

Managerial implications. This study brings Branding 4.0 to managers' attention as a new stage of brand development and provides empirical evidence for its plausible benefits, including customer brand identification, loyalty, long-term competitiveness, and profitability. This paper refines the meaning of Branding 4.0 as requiring brands to provide personalized customer experiences while ensuring the preservation and use of brand elements in product co-design processes. Our findings will help brand managers to better understand the challenges associated with Branding 4.0 implementation and provide them with a "two-tier response strategy"—a plausible theoretical solution drawing on the resource orchestration perspective to support brands in their Branding 4.0 transition. Specifically, the results show that: 1) ML use assists decision makers and managers to make optimal decisions and arrangements; 2) modularity supports maintainability during collaborative design activities; and 3) SCI supports enterprise production flexibility and speed. Managers can therefore consider using all three resources on the first tier to help improve the efficiency of the entire processes from decision-making to delivery. However, our study also found that large amounts of information transferred across levels and departments in the process of providing personalized customer experiences make modularity and SCI vulnerable to the negative impact of information delivery delays. Here, we propose that the interaction of ML with modularity and SCI addresses these negative impacts (the second tier uses ML to support modularity and SCI). Specifically, we suggest that firms and brands shift from a competition view toward a more cooperative approach with downstream and upstream partners focusing on information sharing, synchronized planning, and operational coordination to strengthen their relationships. Firm and brand managers may consider applying ML to enhance activity flows and cooperation. Finally, by embedding ML into modularity, brands will be better able to help customers in their co-design processes by offering more suitable components aligned with customers' diversified needs.

Limitations and future research. While this study expands our understanding of Branding 4.0 and the necessary resources for successful implementation, it also opens multiple paths for future investigation. Firstly, this research reflects the perspectives of managers of B2B and B2C brands in China's garment and footwear industries. Researchers could consider collecting interview data from representatives of other industries such as service industries to obtain a more holistic picture and collective perspective on future strategies for Branding 4.0. Further research may also consider other geographical contexts which are less technologically advanced than China to capture a more balanced perspective on Branding 4.0 challenges. Finally, the largely exploratory nature of this study sets the scene and calls for more quantitative research.

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