What Drives Customer Engagement in Omnichannel Retailing? The Role of Omnichannel Integration, Perceived Fluency, and Perceived Flow

Yang Li and Xiang Gong

***Abstract*—Omnichannel retailers are under intense pressure to harness synergetic management of retail technologies and channels in order to promote customer engagement in the competitive market. Drawing on service-dominant (S-D) logic, we develop a research model to examine how omnichannel integration generates customer engagement through facilitating perceptions of fluency and flow in the shopping experience. We empirically validate the model with a multimethod approach, including an instrument development study to establish the measures of omnichannel integration and a field survey study to validate hypotheses. We find that omnichannel integration has three types: informational integration, transactional integration, and relational integration. These types all positively influence perceived fluency, which further generates customer engagement. Moreover, transactional and relational integration positively influence perceived flow, which ultimately facilitates customer engagement. Our article advances the omnichannel retailing literature by proposing three types of omnichannel integration and developing the S-D logic of customer engagement. Our empirical findings also inform omnichannel retailers about how synergetic technology and channel management in omnichannel integration can be used to promote customer engagement.**

***Index Terms*—Customer engagement, omnichannel integration, omnichannel retailing, service-dominant (S-D) logic, technology-enabled omnichannel marketing.**

I. Introduction

BRICK-AND-MORTAR retailers are pushed to extend their businesses to online channels, whereas online retailers are under pressure to open stores on offline channels [1], [2]. Such synergetic cross-channel retailing is called omnichannel retailing, which refers to the synergetic management of integrating emerging retailing technologies and incorporating all available retailing channels to add value to the customer shopping journey [3], [4]. The global omnichannel market value reached U.S. $2.99 billion in 2017 and is estimated to reach $7.62 billion in 2023, with an annual growth rate of 21.48% [5]. However, omnichannel retailers face an ongoing challenge in recruiting deeply engaged customers. A recent study suggests that about 59% of customers in the U.K. would not download omnichannel retailing apps because they believe such apps do not deliver an integrative cross-channel shopping experience [6]. Therefore, omnichannel retailers should leverage the synergetic management of retail technologies and channels to enhance the productivity of omnichannel integration for driving customer engagement.

Given the importance of this topic, prior omnichannel retailing studies have devoted increasing attention to it [7], [8]. These studies can be broadly divided into two research streams: prescriptive and diagnostic. The prescriptive research stream has uncovered technological solutions for achieving retailers' cross-channel synergy and customers' omnichannel preferences across distinct purchase stages [9], [10]. In contrast, the diagnostic research stream has typically explored drivers of retailers' channel integration strategies and customers' behavioral patterns, with emphasis on the psychological mechanisms by which the omnichannel retailer's integration of technologies and channels affects customers' omnichannel behavior [1], [11]. Although these two research streams have improved the understanding of omnichannel integration and omnichannel customers' behavior, we highlight two issues that require further investigation.

First, prior omnichannel retailing studies have described omnichannel integration using various terms, such as "omnichannel complementarity," "cross-channel integration," "channel integration quality," and "online–offline channel integration" [12]–[15]. These terms are sometimes used interchangeably even though they have different conceptualizations and measures. The inconsistencies between conceptualizations and measures undoubtedly challenge the rigor of the omnichannel retailing literature. Therefore, there is a need to categorize various approaches to omnichannel integration into types and identify recognizable measures of omnichannel integration. Identifying the types of omnichannel integration allows various terms related to omnichannel integration to be clustered into categories without losing sight of the underlying diversity and richness.

Second, the underlying psychological mechanism by which omnichannel integration affects customer engagement has been largely ignored in the omnichannel retailing literature. On the

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Yang Li is with the Hefei University of Technology, Hefei 230002, China (e-mail: yangli@hfut.edu.cn).

Xiang Gong is with the Xi'an Jiaotong University, Xi'an 710049, China (e-mail: xianggong3-c@mail.xjtu.edu.cn).

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one hand, omnichannel integration is likely to facilitate customer engagement through influencing customers' perceptions of fluency in the omnichannel shopping experience [15], which captures utilitarian values such as effectiveness and efficiency in omnichannel service systems. Omnichannel retailers harness the integration of offline and online channels to deliver a seamless and fluent shopping experience. On the other hand, the impact of omnichannel integration on customer engagement is also influenced by the formation of flow in the omnichannel shopping experience [16], which reflects the hedonic value, such as heightened enjoyment and curiosity, experienced when using omnichannel service systems. Studies have argued that the experience of flow can effectively and consistently promote customer engagement in omnichannel activities [17], [18]. Collectively, the experience of fluency and the experience of flow are both important psychological mechanisms by which retailers can harness omnichannel integration to shape customer engagement.

To address the above issues, we develop a research model that explains the impact of omnichannel integration on customer engagement through facilitating the formation of fluency and flow in the omnichannel shopping experience. Guided by the omnichannel retailing literature, we propose three types of omnichannel integration: informational, transactional, and relational. We also build on service-dominant (S-D) logic [19] and propose two types of value-in-context: utilitarian value-in-context, which derives from functional efficiency in using an omnichannel service system, and hedonic value-in-context, which arises from emotional enjoyment in using an omnichannel service system [20]. Applying these concepts to omnichannel retailing, we operationalize utilitarian value-in-context as perceived fluency and hedonic value-in-context as perceived flow. We explain how retailers can harness omnichannel integration to generate customer engagement through facilitating perceived fluency and perceived flow.

II. Theoretical Background

A. Omnichannel Retailing

Omnichannel retailing refers to "the synergetic management of various channels and customer touchpoints to enrich customer value and improve operational efficiency" [4, p. 995]. In omnichannel retailing, brick-and-mortar retailers can leverage preexisting physical assets to bolster the appeal of online channels, whereas online retailers can augment transactional activities by offering and delivering products through offline channels. Our literature review (see APPENDIX A) reveals two predominant categories of omnichannel retailing studies: prescriptive and diagnostic.

The prescriptive studies aim to develop omnichannel technological and business solutions to promote retailers' channel synergies and customers' channel preferences across distinct purchase phases. For instance, Gao and Su [9] proposed virtual showrooms, physical showrooms, and inventory availability information as information mechanisms for achieving channel synergy by influencing customers' channel choices. Jain *et al.* [10] identified cost, attractiveness, accessibility, population characteristics, and expansion possibility as criteria for determining store locations for buy online and pick up in-store (BOPS) service.

The diagnostic studies are descriptive in nature, endeavoring to comprehend reasons behind retailers' integration strategies and customers' behavioral patterns observed in the omnichannel business environment. For instance, Luo *et al.* [14] and Song *et al.* [4] revealed how the complementarity and competition of online/offline stores influence the retailer's total sales based on a panel dataset. Using experimental data from students and Amazon Mechanical Turk (MTurk) workers, Trenz *et al.* [1] and Weber and Maier [11] found that omnichannel integration for acquisition and recovery affects customers' transactional benefits and ultimately their omnichannel service usage. Similarly, Rodriguez-Torrico *et al.* [21] and Xu and Jackson [22] explained omnichannel customers' channel selection by empirically examining the impact of channel characteristics using survey data from MTurk.

Based on our review, we make two observations in terms of research methods and results. First, the prescriptive studies primarily employ analytical modeling with game theory to understand retailers' channel synergies and customers' channel preferences in the omnichannel environment. Meanwhile, the diagnostic studies seek reasons behind retailers' channel strategies and customers' behavioral patterns in omnichannel retailing. While most prescriptive studies use a single empirical dataset, diagnostic studies generally use multiple datasets to seek reasons behind retailers' channel strategies and customers' behavioral patterns. This article, in contrast, advances the methodological understanding of omnichannel retailing by using a multimethod approach that includes an instrument development study and a field survey study. Second, although prior studies have recognized the value of omnichannel integration, the conceptualizations and measures of it still lack systematic investigation. Meanwhile, limited studies have examined the psychological mechanisms by which omnichannel integration can be harnessed by retailers to shape customer engagement. This article enriches the theoretical understanding of omnichannel retailing by delineating its types, developing measures for it, and specifying the effect it has on customer engagement through fostering perceptions of fluency and flow.

B. Omnichannel Integration

Omnichannel integration refers to "the synergies between online and offline channels to broaden the range of service options beyond what is feasible via either channel" [1, p. 1208]. In contrast with maintaining two separate channels, the technological integration of offline channels (e.g., physical store and after-sales service point) and online channels (e.g., website, mobile app, self-service technology, and social media) provides customers with a seamless shopping experience. Various terms have been used interchangeably to describe omnichannel integration, such as "omnichannel complementarity," "cross-channel integration," "channel integration quality," and "online-offline channel integration," with "omnichannel integration" being the term most frequently used by researchers [1], [11], [23], [24]. These inconsistent conceptualizations and measures of omnichannel integration challenge the rigor of findings in the existing literature. In this article, we theoretically conceptualize omnichannel integration into three types: informational integration, transactional integration, and relational integration. In our literature review (see APPENDIX B), we found that omnichannel retailers' informational, transactional, and relational integration have been defined differently in terms of value propositions to influence customer experience and customer behavior.

Informational integration refers to the extent to which one channel provides retail information (e.g., brand, product, sales network, and service procedures) about and access to another channel. It has been identified as information mechanism [9], online–offline channel integration [25], integrated marketing communication [26], and integrated omnichannel targeting [27]. This type of omnichannel integration ensures accessibility, connectivity, and consistency when customers search in an omnichannel environment. Informational integration subsumes the concept of information quality for customers' omnichannel service usage. For instance, Gao and Su [9] proposed physical showrooms, virtual showrooms, and inventory availability information as the information mechanisms that can help customers reduce product value uncertainty and availability risk. Herhausen *et al.* [25] highlighted the influence of informational integration in reducing customers' perceived risk of online purchase. Therefore, informational integration reflects omnichannel retailers' value proposition of offering high-quality information to improve customers' decision-making experience before purchase.

Transactional integration refers to the degree to which one channel provides fulfillment functions (e.g., coupon redemption, payment, order tracking, returning, and after-sales support) for and access to another channel. It has been labeled as omnichannel integration for acquisition and recovery [1], physical integration [28], integration of customer order fulfillment [35], and ship-to-store service [30]. This type of omnichannel integration is characterized by mutuality, complementarity, and reciprocity when customers receive services from omnichannel retailers. Transactional integration is aligned with the proposition of service quality in omnichannel service systems. For instance, Trenz *et al.* [1] proposed pick up in-store and service-in-store as two forms of omnichannel integration services to help customers complete the online transaction process using the supportive functionalities of offline stores. Bendoly *et al.* [28] defined transactional integration as the extent to which one channel provides mutual support for customers to conduct transactions in other channels. Therefore, transactional integration reflects omnichannel retailers' value proposition of offering convenient service to facilitate customers' transaction experiences during purchase.

Relational integration refers to the degree to which a firm incorporates customer information (e.g., basic demographics, preferences, purchase histories, and cookies) into the firm's operations and provides customization in online and offline channels. It has been proposed as customization [31], relational information integration [32], and personalized incentive [33]. This type of omnichannel integration emphasizes customization, personalization, and individualization of cross-channel

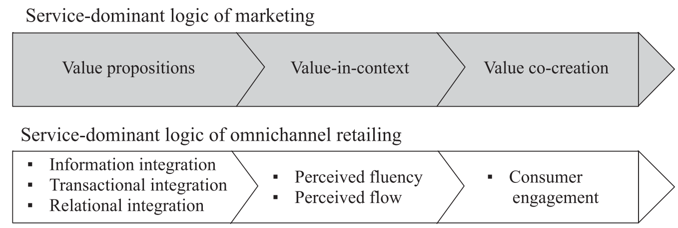

Fig. 1. Service-dominant logic of omnichannel retailing.

reconfigurations for customers' personal interests. Relational integration coincides with a customer-centric view of technology management. For instance, Jayachandran *et al.* [32] proposed relational integration as the approach for implementing a customer-centric management system and examined its impact on customer relationship performance. Hsia *et al.* [33] highlighted the role of personalized incentives in enhancing customers' situation involvement and service experience in omnichannel retailing. Therefore, relational integration reflects the omnichannel retailers' value propositions of offering customer-centric service systems to promote customer relationships beyond the one-time purchase.

C. Service-Dominant Logic

According to S-D logic, the focus of a firm shifts from the provision of tangible resources to the leverage of intangible resources for the purpose of achieving value cocreation with customers [19]. The concepts of value propositions, value-in-context, and value cocreation are fundamental pillars of S-D logic (see Fig. 1). Value propositions refer to a service provider's (i.e., omnichannel retailer's) offering of unique resources (i.e., website, physical stores, mobile apps, and brand-hosted social media) that invite customers to derive value from engagement in the provider's cocreation activities (i.e., omnichannel integration) [34]. In omnichannel retailing, value propositions connect an omnichannel retailer with customers interested in the unique resource within the omnichannel service system [20]. Developing a compelling value proposition (i.e., customer-centric omnichannel integration) ensures omnichannel retailers perform their best in catering to customers' interests [7]. According to S-D logic, omnichannel integration is the key value proposition offered by omnichannel retailers to engage customers in value cocreation [35].

Value-in-context refers to the phenomenological perspective of value in which value is always uniquely and contextually derived in service systems. In S-D logic, value-in-context can be either utilitarian or hedonic. As a typical form of utilitarian value-in-context in omnichannel retailing, perceived fluency refers to the subjective experience of feeling ease or difficulty in any form of mental processing [36]. It indicates high service quality [37] and usability [38] of the omnichannel service system. As a representative form of hedonic value-in-context in omnichannel retailing, perceived flow is defined as the enjoyable and optimal experience of interacting with the omnichannel service system. It reflects the psychological state of total involvement and deep attention in system interaction. Integrating virtual and physical

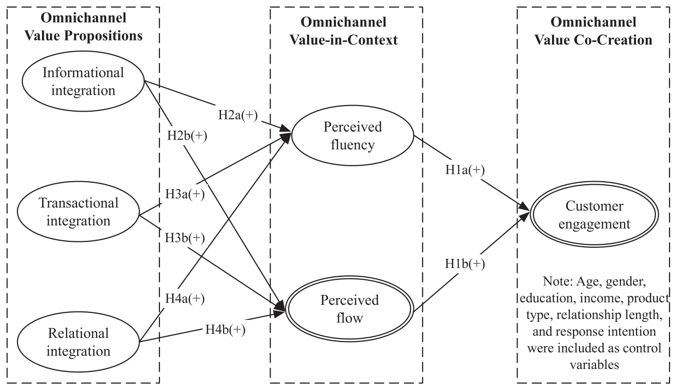

Fig. 2. Research model.

channels increases the possibility of fostering fluency and flow states in omnichannel retailing [15], [16].

Value cocreation refers to the value cocreated by the service provider (e.g., omnichannel retailer) and the service beneficiary (e.g., customers) through resource integration (e.g., omnichannel integration) within a service system. In the omnichannel service system, value cocreation occurs when customers take actions to engage in integrating retailer-provided resources (e.g., the unique capabilities of the employed channels) and their private resources (e.g., skills and assets to use the channels effectively in particular situations). According to S-D logic, a typical value cocreation action is customer engagement, which refers to "the mechanics of a customer's value added to the firm, either through direct or/and indirect contribution" [7].

III. Research Framework and Hypotheses

Fig. 2 depicts the research model. Grounded in S-D logic [19], we operationalized omnichannel value propositions as informational, transactional, and relational integration; omnichannel value-in-context as perceived fluency and perceived flow; and omnichannel value cocreation as customer engagement. We investigated how omnichannel integration promotes customer engagement by influencing the formation of perceived fluency and perceived flow. We also added age, gender, education, income, product type, relationship length, and response intention as control variables.

A. Effects of Perceived Fluency and Perceived Flow on Customer Engagement

Cognitive theories have emphasized the importance of saving time and effort in encouraging customers' sustained behavior within a system [42]. Fluency has been shown to reflect the effectiveness of online advertising in promoting customer purchases in the human–computer interaction setting [39]. In the omnichannel service system, perceived fluency indicates the degree of ease or difficulty in information processing [43], task migration, and platform transition [38] across channels. It satisfies omnichannel customers' expectations of a seamless shopping experience, thereby increasing their usage of omnichannel service systems [15]. Perceived fluency has also been shown to represent an effortless and effective state in channel activities that can motivate customers to engage in exploratory behaviors [44] like making online purchases [45] or sharing shopping experiences on social media [46]. In terms of integrated channels and customer touchpoints, omnichannel service systems provide customers with opportunities to seamlessly switch between and explore both virtual and physical channels. Thus, perceived fluency increases the likelihood of promoting customer engagement in the omnichannel environment.

H1a: Perceived fluency is positively related to customer engagement.

Prior research has suggested that perceived flow represents a psychological state characterized by concentration, control, and enjoyment while doing online activities [47]. It is an inviting and enjoyable experience pursued by customers [48]. As the optimal experience in online environments, perceived flow influences a wide range of customer behaviors, including purchasing products, providing feedback, and giving recommendations [18]. For instance, perceived flow reflects a customer's attention and focus on digital technologies that increase customer engagement by addressing the issue of immediacy. Perceived flow can also indicate a customer's control over mobile shopping [49] and their enjoyment of social media interactions [50], both of which encourage customer engagement to repeat the flow state. Digital technologies and activities are integrated into omnichannel service systems to promote the experience of flow by empowering customers to persistently interact with the integrated omnichannel activities. Thus, perceived flow represents a customer's affective response to the omnichannel service system, which can sustain customer engagement over time.

H1b: Perceived flow is positively related to customer engagement.

B. Effects of Informational Integration on Perceived Fluency and Perceived Flow

Informational integration refers to the coordination of communication across channels in order to provide customer access to product or service information. Prior studies have argued that incidental exposure to advertisement information increases fluency by impressing information on the customer's memory [51]. Repeat messages and marketing promotions in different channels have been viewed as incidental exposure to product or brand advertisements [52], which should increase fluency when customers process familiar information [15]. Informational integration also increases the level of congruence between virtual and physical channels [53]. For example, image congruence advances fluent experience by reducing a customer's effort in processing information from different sources. Moreover, mobile assistants and self-service technologies in omnichannel systems promote the experience of fluency by saving customers time in searching [54].

H2a: Informational integration is positively related to perceived fluency.

Perceived flow has been posited as the result of informational integration in virtual and physical channels [55]. It refers to seamless cross-channel experiences that customers can control [56]. For instance, the same brand image and product information in different channels can provide customers with a consistent shopping experience [57]. Both virtual and physical customers can thus generate a flow state via enhanced control and focused attention in the cross-channel interface [18]. Additionally, omnichannel service systems involve self-service technologies and value-added search functions that enhance customers' experience of flow by increasing their interactivity in the omnichannel service system [58].

H2b: Informational integration is positively related to perceived flow.

C. Effects of Transactional Integration on Perceived Fluency and Perceived Flow

Transactional integration refers to the consolidation of purchase-related functions in different channels that facilitate customers' transactions. Prior studies have found that transactional integration, such as BOPS service, can display real-time inventory availability information for physical stores in certain areas, and this influences customers' inferences about the channel's service convenience [10] and their decision to purchase through the channel [59]. Accordingly, transactional integration can increase fluency because customers' involvement in functional information increases their level of attention input and their intention to proceed with a transaction [60]. Moreover, the integration of virtual information and physical fulfillment functions provides customers with the option to complete transactions at their convenience. In such cases, integrated interactions can increase perceived fluency by facilitating decision-making processes and task migration from one channel to another [15].

H3a: Transactional integration is positively related to perceived fluency.

Additionally, transactional integration has been posited as an important manifestation of an omnichannel retailer's service quality [35]. For example, a key feature of perceived flow, enjoyment, can be induced by perceived service quality [61]. The convenience of self-collecting online orders and the reliability of postpurchase support together represent service quality provided by transaction process integration [62]. Further, cross-channel service convenience increases customers' self-efficacy in their interactions with different channels, which is another important precondition for the experience of flow [58].

H3b: Transactional integration is positively related to perceived flow.

D. Effects of Relational Integration on Perceived Fluency and Perceived Flow

Relational integration refers to the incorporation of customer information into a firm's operation of communications and transactions. Previous studies have found that a message's personal relevance can prompt individuals to use recalled content and can facilitate fluency in judgment processes [63]. The feeling of fluency can also be reinforced by persuasive communication, such as the repetition of familiar information [64]. When personal preferences and transaction histories are integrated into customers' shopping activities, the increased relevance of shopping tasks and the channel's seeming familiarity with their personal tastes can increase customers' perception of fluency. Furthermore, customized communications and transactions promote perceived fluency by reducing the amount of effort and time needed to process experiential attributes [39].

H4a: Relational integration is positively related to perceived fluency.

In addition, relational integration has been shown to induce perceived flow through the mechanism of customized offerings [65] and value-added search functions [47]. Customized benefits like personalized recommendations and member-owned rights reflect omnichannel customers' pursued value and therefore attract their attention and interest. Moreover, providing personalized benefits is important for building customer trust as a foundation for promoting online behaviors [40]. By infusing customer value into omnichannel information and transactions, businesses can generate a flow state that is enjoyable for customers. Omnichannel customers also pursue value-added search functions to enhance their control over different channels. Thus, integrating customer needs and preferences should increase perceived flow by ensuring the continuity and connectivity of the omnichannel experience.

H4b: Relational integration is positively related to perceived flow.

We used a multimethod approach with two empirical studies to validate the research model. Study 1 was an instrument development process to create scales for omnichannel integration and its three types. Study 2 was a follow-up field survey to test the research model and hypotheses in an omnichannel retailing field setting. The two empirical studies collectively help us establish integrative findings and robust inferences.

IV. Study 1: Instrument Development Study

The objective of Study 1 was to seek qualitative evidence for the proposed three types of omnichannel integration. According to the classical instrument development process [66], we developed the scales of omnichannel integration with three stages. In stage 1, we performed item generation to identify an initial pool of items pertinent to the omnichannel retailing context. In stage 2, we conducted scale development to differentiate the types and scales of omnichannel integration using two-round card sorting. In stage 3, we used instrument testing to examine the reliability and validity of our model of omnichannel integration.

A. Item Generation

In the item generation stage, we identified a pool of items to measure the three types of omnichannel integration, informational, transactional, and relational [67], and determine the items through domain specificity, item collection, and item refinement.

Domain specificity: Specifying the theoretical domain of omnichannel integration is important when generating a pool of items pertinent to omnichannel retailing [68]. Domain specificity focuses on identifying what should be included and excluded in defining omnichannel integration. To advance customer engagement in omnichannel retailing, scholars propose that omnichannel integration should adopt a customer-centric view [7]. Specifically, the customer-centric view of technology management emphasizes the integration of actions that a firm carries out in order to meet customers' needs [32], including high-quality communication content, convenient transaction process, and close relationship building [69]. We accordingly submit that customer-centric omnichannel integration could be specified as the actions a firm undertakes to ensure front-end customer interactions through informational, transactional, and relational integration.

Item collection: We generated the sampling items by performing a literature review on omnichannel integration and observing omnichannel brands in public media. That is, we initially gathered the items for omnichannel integration by reviewing previously validated scales from the existing omnichannel integration literature. We also collected descriptive sentences about omnichannel integration by observing the practices of leading retailers who reported their omnichannel strategy publicly in annual reports [35]. Collectively, we got a total of 18 items for omnichannel integration.

Item refinement: To improve the content validity of omnichannel integration, we invited six subject matter experts who were familiar with the topic of omnichannel retailing to review and revise the generated scales. We provided the experts with the conceptual definitions and contextual illustrations of omnichannel integration and its types (see Table C1). The experts were asked to check the corresponding items for omnichannel integration and tag problematic items. Consequently, the item refinement process resulted in 15 appropriate items and three problematic items. The three problematic items were repeatedly modified until the experts reached a consensus.

B. Scale Development

In the scale development stage, we performed two-round card sorting to improve the reliability and validity of our omnichannel integration measures using a card sorting questionnaire [67]. This questionnaire involved three sections (Table C2): section I offered 18 items identified in the item generation stage; section II presented the construct name, entity, general property, and conceptual definition; and section III provided space for judges to express their feedback and provide suggestions for improving any ambiguous descriptions.

We checked the item placement ratio, Cohen's kappa, and content validity to validate the card sorting process. The cutoff values for item placement ratio, Cohen's kappa, and content validity were 0.65, 0.60, and 0.60, respectively [70]. Item placement ratio reflects the extent to which judges reach a consensus on the categorization of items in appropriate dimensions [70]. Cohen's kappa was originally proposed by Moore and Benbasat [70] to measure the level of agreement between two judges who independently classify specific items into three mutually exclusive categories. It reveals the degree of agreement among judges in sorting items and has been widely used to assess the reliability of the card sorting process. For example, Sun [71] reported average Cohen's kappa values of 0.77 and 0.85 in the first and second round of card sorting, respectively, related to herding behavior. Jiang *et al.* [67] suggested that the average Cohen's kappa for the card sorting process related to perceived website aesthetic was 0.70. Likewise, Liang *et al.* [72] argued that the average Cohen's kappa for the card sorting process related to emotion-focused coping was 0.92. Content validity was tested by asking the judges to rate the degree to which selected items reflected the definition of their intended dimension using a five-point Likert scale where 1 = not at all and 5 = completely [73].

First-round card sorting: We invited seven judges to evaluate the generated items in the first-round card sorting [70]. Although different standards for the acceptable number of judges for card sorting in the scale development process exist, the literature commonly considers five to ten judges to be sufficient to provide theoretical rigor and practical relevance. For example, Liang *et al.* [72] recruited five judges to divide twenty items into five dimensions of emotion-focused coping. Thatcher *et al.* [74] invited five judges to sort twelve items into the four dimensions of IT mindfulness. Similarly, Sun [71] asked eight judges to participate in the card sorting process when developing the scales of herding behavior. Jiang *et al.* [67] sorted 32 items into 5 dimensions of perceived website aesthetic with 10 judges. As shown in Tables C3 and C4, Cohen's kappa ranged from 0.72 to 0.88, which was higher than the suggested cutoff value of 0.65; item placement ratio and content validity were greater than the threshold value of 0.60, except for II5, TI1, and RI1, which were subsequently removed. After this stage, we retained 15 items for omnichannel integration.

Second-round card sorting: We conducted the second-round card sorting by inviting a new group of seven judges to categorize the remaining fifteen items into their intended types. As previously, we checked the item placement ratio, Cohen's kappa, and content validity using the second-round data. As shown in Tables C3 and C4, Cohen's kappa was higher than 0.90 and the item placement ratio exceeded 0.85, which demonstrates a high consensus among judges regarding the categorization of items. As for content validity, all items were validated by reaching and exceeding 0.80. The confirmed 15 items with qualified reliability and validity were further tested in the following instrument testing stage.

C. Instrument Testing

In the instrument testing stage, we validated the scales of omnichannel integration using a data sample of 128 customers [67]. We conducted exploratory factor analysis, confirmatory factor analysis, and nomological validity analysis to evaluate the psychometric properties of the newly developed measure of omnichannel integration.

Exploratory factor analysis: Initially, we performed Kaiser–Olkin (KMO) and Bartlett's tests using SPSS 20 to conduct descriptive factor analysis [75]. The result of the KMO test was 0.87 and Bartlett's test of sphericity was significant at $p = 0.00$, thereby demonstrating the adequacy of the data sample for exploratory factor analysis. Then, principal component analysis of 15 items was conducted with varimax rotation, resulting in three separate factors. Given the threshold value of factorial loading above 0.60, II2 and TI2 in Table C2 were excluded from the items list. We then validated scales of the remaining 13 items for internal reliability, convergent validity, and discriminant validity [75]. As Table C5 reports, the average variance extracted (AVE) values were higher than 0.50, the composite reliability (CR) values were greater than 0.85, and the Cronbach's alpha ranged from 0.80 to 0.85, which is higher than the threshold value of 0.7 [76]; therefore, internal reliability was satisfactory. Meanwhile, factorial loadings were higher than 0.70, so convergent validity was acceptable. The correlations among informational integration, transactional integration, and relational integration ranged from 0.50 to 0.62, and the square roots of AVEs were higher than intraconstruct correlations, suggesting that the constructs' discriminate validity was satisfactory [77].

Confirmatory factor analysis: We checked the model fit of the omnichannel integration scale by conducting confirmatory factor analysis using LISREL 8.7. Three alternative models were estimated. In model 1, omnichannel integration was operationalized as a unidimensional construct using 13 items. In model 2, omnichannel integration was conceptualized as a second-order formative construct consisting of three types: informational, transactional, and relational integration. In model 3, informational, transactional, and relational integration were fragmented as first-order reflective constructs. As shown in Table C6, the fit of model 3 ($\chi^2(62) = 114.62$, $p = 0.00$, CFI $= 0.96$, IFI $= 0.96$, NFI $= 0.92$, NNFI $= 0.95$, RMSEA $= 0.08$) was considerably better than that of model 1 ($\chi^2(65) = 270.47$, $p = 0.00$, CFI $=$ 0.89, IFI $= 0.89$, NFI $= 0.86$, NNFI $= 0.87$, RMSEA $= 0.15$) or model 2 ($\chi^2(63) = 129.20$, $p = 0.00$, CFI $= 0.95$, IFI $=$ 0.95, NFI $= 0.91$, NNFI $= 0.93$, RMSEA $= 0.09$). Therefore, we considered the first-order reflective construct adequate for indicating the factor structure of omnichannel integration scales.

Nomological validity analysis: We demonstrated nomological validity by conducting partial least squares structural equation modeling (PLS-SEM) using SmartPLS 3, which is preferred due to the small sample size [78]. Three alternative models were estimated. In model 1, omnichannel integration was operationalized as a reflective construct to influence perceived fluency, perceived flow, and customer engagement. In model 2, omnichannel integration was conceptualized as a second-order formative construct to exert influence on perceived fluency, perceived flow, and customer engagement. In model 3, informational, transactional, and relational integration were theorized separately as first-order reflective constructs to affect perceived fluency, perceived flow, and customer engagement. The results of model 1 and model 2 showed that the R2 values for perceived fluency were below 0.2 when omnichannel integration served as an independent variable. Meanwhile, the results of model 3 indicated that the R2 values for perceived fluency, perceived flow, and customer engagement were 0.21, 0.27, and 0.41, respectively, therefore suggesting that model 3 fits the data well. Thus, we concluded that model 3 demonstrates satisfactory nomological validity.

V. Study 2: Online Survey

A. Sample and Data Collection

We collected online survey data from MTurk during a time window of one month from January 16 to February 20, 2019. MTurk is the most popular crowdsourcing destination among behavioral researchers and serves as a particularly useful platform for conducting omnichannel retailing research [79] for several reasons. First, omnichannel retailing is a topic of general customer interest for which no special expertise is needed. Using MTurk allows us to efficiently access respondents from a wide range of sociodemographic backgrounds. Second, omnichannel retailing involves many customers with specific traits (e.g., prior cross-channel shopping experience). MTurk is effective in recruiting respondents with preferred characteristics using multiple advance-screening questions. Third, prior omnichannel retailing studies have increasingly relied on MTurk, making it a common way to recruit respondents and collect self-reported data [21], [22].

Given the sensitive socioeconomic nature of the MTurk sample, we implemented several procedural remedies taken from the latest MTurk methodological literature to ensure the representativeness of our data sample [80]. First, we used multiple data screening procedures to ensure participants were active omnichannel customers, including checking their multichannel experience, cross-channel usage, and omnichannel brand experience. Second, we recruited diverse omnichannel customers through the provision and selection of various representative brands with omnichannel practices. We identified 25 well-known brands for potential respondents to select according to their actual shopping experience. These brands all have online and offline retail channels in the United States that can be accessed by the potential respondents from MTurk. We confirmed the selected brands' omnichannel integration services through visiting their official websites and browsing their annual reports [35]. Third, we used the MTurk technical options to make the survey available only to respondents who had completed less than 10 surveys on MTurk, which eliminated professional survey-takers with purely financial incentives. Fourth, we randomly inserted attention check questions throughout the questionnaire to ensure that respondents would not provide careless, random, or haphazard responses [81]. We provided \$2 as monetary compensation for respondents who passed the validation and attention checks.

We also used several statistical remedies, following the leading practices for MTurk studies, to verify the representativeness of our data sample [80]. First, we employed a high degree of data filtering through analyzing the respondents' omnichannel experience. Overall, 335 complete responses were received and 108 invalid samples from individuals with little omnichannel experience were removed, leaving 227 valid samples. Second, we performed the demographic profile comparison analysis and found that our data sample was comparable in gender, age, education, and monthly income with the distribution of omnichannel customers in prior studies (Table D1). Of 227 respondents, 56.80% were male, 80.20% were aged 30 or above, 70.50% had a bachelor's degree or above, and 78.90% had a monthly income below \$5001. In terms of the brands that respondents selected, 52.42% were apparel brands and 47.58% were technology brands. In terms of omnichannel shopping experiences, 70.90% of respondents had searched the selected brands online and purchased their products offline, whereas 29.10% had searched the selected brands offline and purchased their products online. In terms of relationship length, 98.2% of respondents were familiar with the selected brands for at least 1 year. In terms of geographic regions, 72.24% came from the

United States, 17.20% from India, and 10.56% from anonymous addresses. Third, due to the potential economic differences, we conducted a *t*-test to compare the monthly income of respondents from the United States ($n = 164$) and India ($n = 39$). The results showed that there was no significant difference in the two groups ($t = 0.50$, $p = 0.61$). Fourth, we incorporated the sociodemographic differences of respondents into the model to alleviate the potential influence of socioeconomic status in omnichannel retailing.

B. Measures

To ensure that respondents engaged with their past shopping experiences in the omnichannel retailing setting when answering relevant survey questions, we used a recall method to induce respondents' perceptions of a recent omnichannel shopping experience with a target brand (see APPENDIX E). The recall method is based on instrumental survey prompts and logic and works efficiently in retrieving customers' long-term memories, where they store their knowledge specific to their past shopping experiences [82]. To access participants' most recent remembered shopping experiences, we asked them to think of their recent omnichannel shopping experience with a brand (e.g., searching the online store and purchasing at the physical store or searching the physical store and purchasing in the online store). We also required them to select the brand name and write down the product price information to facilitate the retrieval of their remembered shopping experience. We believe that this recall method is particularly helpful in the omnichannel retailing setting because customers often recall their integrated offline and online shopping experiences when they engage in value cocreation with the omnichannel brand. Collectively, the survey measures involved two parts: measures related to general constructs and measures related to principal constructs.

To measure omnichannel integration, a four-item scale for informational integration, a four-item scale for transactional integration, and a five-item scale for relational integration were developed as first-order reflective constructs based on our instrument development study. We conceptualized perceived fluency as customers' subjective feeling of ease or difficulty when mentally processing information and services during an omnichannel shopping experience. Congruent with prior studies [36], [40], we conceptualized perceived fluency as a first-order reflective construct in which the items are covaried and interchangeable with each other, have similar predictors, and reflectively manifest the construct. The five-item scale for perceived fluency was adapted from Graf *et al.* [36]. We conceptualized perceived flow as a second-order formative construct consisting of perceived temporal dissociation, perceived immersion, perceived enjoyment, perceived control, and perceived curiosity. We used perceived flow to indicate customers' state of deep involvement with the omnichannel service system. The measurement scale for each subdimension of perceived flow was adapted from Agarwal and Karahanna [41]. We conceptualized customer engagement as a second-order formative construct that includes four dimensions, i.e., customer purchase, customer reference, customer influence, and customer knowledge. We used customer engagement to indicate customers' behavioral manifestations that can create value for firms through transactional and nontransactional activities [83]. Each dimension of customer engagement was measured by a four-item scale adapted from Eisingerich *et al.* [84] and Kumar and Pansari [83].

We included gender, age, education, personal monthly income, product type, brand relationship length, and follow-up survey intention as the control variables [85], [86]. Gender was measured by one item where 1 = male and 2 = female. Age was measured by a seven-point scale ranging from 1 = 18–23 to 7 = 50–55. Education was measured on a five-point scale ranging from 1 = high school and below to 5 = post-graduate and above. Monthly income was measured using a five-point scale from 1 $= \leq 1000$ to $5 \geq 7000$. Brand relationship length was measured by one question asking how long the respondent has known the brand. Product type was measured by manually classifying the reported product name as 1 = search product or 2 = experience product. Likewise, follow-up survey intention was measured by one indicator asking whether the respondent was willing to participate in a follow-up survey. The marker variable, i.e., collectivism, was measured by four items adapted from George *et al.* [87]. To address potential concerns about using perceptual measures and self-reported data, we conducted analyses related to nonresponse bias, sample self-selection bias, and common method bias (see APPENDIX F). The results showed that these biases were not serious concerns in this article.

C. Result

We validated the research model using PLS-SEM. PLS-SEM has been widely used in the existing literature for handling complex models with both reflective and formative constructs [88]. Moreover, PLS-SEM works efficiently in modeling relatively small samples (e.g., below 250) with stable statistical quality [88]. We first adopted the indicator reuse approach by computing PLS algorithms to calculate the latent variable score of first-order reflective constructs, which were then used as the indicator of second-order formative constructs [89].

Measurement model: We validated the measurement model of first-order reflective constructs in terms of internal reliability, i.e., Cronbach's alpha > 0.70, CR > 0.70, AVE > 0.50, convergent validity, i.e., loadings > 0.60, and discriminant validity, i.e., square roots of the AVEs $>$ construct correlations [90]. As shown in Table D2, Cronbach's alpha ranged from 0.71 to 0.97, the CR ranged from 0.82 to 0.97, and the AVE ranged from 0.53 to 0.91, thereby indicating satisfactory internal reliability. Moreover, the item loadings ranged from 0.67 to 0.96, thereby suggesting acceptable convergent validity. As shown in Table D3, discriminant validity was established because the square roots of AVEs for all constructs were greater than construct correlations. We validated the measurement model of second-order formative constructs in terms of weight size and weight significance [91]. The size and significance of formative indicators' weight reveal their respective roles in significantly determining the formation of a formative construct. As Table D4 indicates, all formative indicators had statistically significant weights with acceptable weight sizes.

Multicollinearity refers to a situation where predictors are highly correlated with each other [92]. To check for

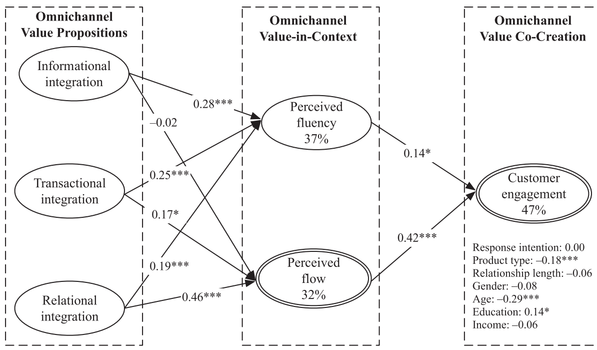

Fig. 3. Structural model.

multicollinearity, we performed a multicollinearity test with the variance inflation factors (VIFs). Prior research has proposed different standards of acceptable VIFs for assessing the existence of multicollinearity, such as 10.00 for reflective indicators and 3.33 for formative indicators, with lower values being better [91]. Moreover, the tolerance for both reflective and formative indicators should be higher than 0.10. As Table D2 shows, all VIFs were below 10.00 and all tolerances were higher than 0.10 for reflective constructs. Table D4 shows that all VIFs were lower than 3.33 and all tolerances were greater than 0.10 for formative constructs. These results indicate that multicollinearity is not a major concern in this article.

Structural model: As shown in Fig. 3, perceived fluency ($\beta = 0.14$, $p = 0.01$) and perceived flow ($\beta = 0.42$, $p = 0.00$) significantly and positively affected customer engagement, thereby confirming H1a and H1b. Furthermore, informational integration ($\beta = 0.28$, $p = 0.00$), transactional integration ($\beta = 0.25$, $p = 0.00$), and relational integration ($\beta = 0.19$, $p = 0.01$) were positively associated with perceived fluency, thereby supporting H2a, H3a, and H4a. In contrast to our expectation, the effect of informational integration ($\beta = –0.02$, $p = 0.76$) on perceived flow was nonsignificant, so H2b was rejected. Transactional integration ($\beta = 0.17$, $p = 0.04$) and relational integration ($\beta = 0.46$, $p = 0.00$) were positively related to perceived flow. Hence, H3b and H4b were supported. The R2 values for perceived fluency, perceived flow, and customer engagement were 0.37, 0.32, and 0.47, respectively, which suggests a good fit of the overall structural model. We further conducted a series of *post-hoc* analyses (see APPENDIX G) to demonstrate the robustness of our research findings.

VI. Discussion and Implications

This article seeks to understand the formation of customer engagement in omnichannel retailing. Drawing on S-D logic, we operationalized omnichannel value propositions as omnichannel integration; omnichannel value-in-context as perceived fluency and perceived flow; and omnichannel value cocreation as customer engagement. We theoretically proposed that omnichannel integration can be clustered into three types: informational integration, transactional integration, and relational integration. We developed a model to explain how omnichannel integration promotes customer engagement through the formation of perceived fluency and perceived flow in omnichannel retailing. We initially conducted an instrument development study to identify the types and scales for omnichannel integration, followed by a field survey study to validate the model. The empirical results supported most hypotheses in the model and offer several key findings.

First, informational, transactional, and relational integration are positively related to perceived fluency, which further leads to customer engagement (H1a, H2a, H3a, and H4a supported). Prior omnichannel retailing studies have recognized the value of integration between offline and online channels in shaping customer behavior [1], [2]. However, the underlying mechanism by which omnichannel integration explains customer engagement has been largely ignored. Our article confirms the positive relationship between omnichannel integration and customer engagement (i.e., purchase, reference, influence, and knowledge) in omnichannel retailing. Moreover, our article shows that omnichannel integration is positively associated with customer engagement through the formation of fluent shopping experience. Customers are likely to engage in the omnichannel service system when omnichannel integration eases the process of their interaction and transaction activities performed across channels.

Second, transactional and relational integration are positively related to perceived flow, which ultimately facilitates customer engagement (H1b, H3b, and H4b supported). Thus, omnichannel retailers can harness the omnichannel integration services of the transaction process and customer relationship to improve customers' flow during the shopping experience and their behavioral engagement in the omnichannel service system. On the contrary, informational integration has a nonsignificant correlation with perceived flow (H2b rejected). One plausible explanation for this surprising and unexpected result is that the relationship between informational integration and perceived flow may be fully mediated by perceived fluency. Our mediation analysis further suggested that the indirect effect of informational integration through perceived fluency on perceived flow was significant ($\beta = 0.07$, $\text{CI}_{95\%} = [0.0250, 0.1436]$, $p = 0.02$), while the direct effect of informational integration on perceived flow was nonsignificant ($\beta = –0.09$, $\text{CI}_{95\%} = [0.2533, 0.0613]$, $p = 0.24$), which indicates a full mediating effect of perceived fluency in the relationship between informational integration and perceived flow. Prior research has found that utilitarian rewards of using technologies are key determinants of the flow state [93]. That is, information integration provides customers a fluent and effortless shopping experience across channels, which serves as an important utilitarian reward to drive their flow during the omnichannel retailing shopping experience.

A. Theoretical Implications

This article contributes to the understanding of synergetic management of technologies and channels in omnichannel retailing. First, our article advances the channel integration enactment in omnichannel retailing by identifying the types of omnichannel integration and developing measures for each type of it. Omnichannel integration allows for the integration of emerging technologies and retailing channels, which develops a firm's capability to deliver a seamless cross-channel shopping experience [4], [8]. Additionally, omnichannel integration demonstrates the synergetic technology management of offline and online channels to enhance a firm's productivity in value cocreation with customers [3], [10]. Prior studies have described omnichannel integration using various terminologies interchangeably [1], [4], [12], [59], without a systematic classification of how various omnichannel integration types resemble or differ from each other. To facilitate the application of innovative cross-channel retail technologies in effectively managing channel resources, we conceptualize omnichannel integration into three types: informational integration, transactional integration, and relational integration. Moreover, we develop instruments for each type of omnichannel integration. Therefore, our article helps researchers characterize and distinguish different types of omnichannel integration and serves as a basis for future research exploring omnichannel integration strategies.

Second, our article enriches the omnichannel customer behavior literature by uncovering the underlying psychological mechanisms by which omnichannel integration shapes customer engagement. Prior omnichannel retailing studies constitute two predominant research streams: prescriptive and diagnostic [94]. Despite recognizing the value of omnichannel integration in promoting customers' omnichannel behavior, both diagnostic and prescriptive studies fail to elucidate how omnichannel integration can be harnessed by retailers to shape customer engagement. Our article bridges the knowledge gap by positioning fluency and flow in the shopping experience as the underlying psychological mechanisms that link omnichannel integration to customer engagement. This investigation of perceived fluency and perceived flow advances the theoretical understanding of integrating cross-channel retail technologies for promoting the productivity of value cocreation between the omnichannel retailer and customers [3], [10]. Our empirical findings shed light on the effective management of technologies and channels in promoting fluency and flow in the shopping experience in the omnichannel service system.

Third, our article develops an S-D logic-based model of omnichannel service systems and enhances the contextual operationalization of core concepts in S-D logic. Specifically, we contextualize value propositions as omnichannel integration, value-in-context as perceived fluency and perceived flow, and value cocreation as customer engagement in omnichannel retailing. Prior studies have applied S-D logic to examine the engineering and technology management issues in various service systems, such as product-service systems [95], open innovation systems [96], and software ecosystems [97]. To the best of our knowledge, few studies have extended S-D logic to investigate the technology and channel management issues in omnichannel service systems. S-D logic offers us a novel theoretical perspective for explaining how the systematic management of cross-channel retail technologies facilitates omnichannel retailers' value cocreation with customers. Our contextual conceptualizations of omnichannel integration, customer experience, and customer engagement progressively demonstrate the potential for the key concepts in S-D logic to be operationalized and tested in the context of omnichannel service systems.

B. Practical Implications

This article has several implications for retailers' omnichannel business success, especially regarding the management of channel integration strategies and customer behavior. First, our article directs omnichannel retailers' attention to the strategic management of customer engagement. The global omnichannel retail market is undergoing rapid technological evolution and intense competition. Promoting customer engagement is crucial for omnichannel retailers to gain a competitive advantage in the omnichannel retail market. Based on the conceptualizations and dimensions of customer engagement, we recommend that omnichannel retailers focus on driving customer engagement in terms of purchase, reference, influence, and knowledge. To increase customer purchases, retailers could draw on either efficiency improvement or hedonic design of omnichannel service systems. To facilitate customer reference, retailers are advised to be cautious in using monetary benefits, which may generate social risk in omnichannel customer social networks [84]. To leverage customer influence, retailers should maximize the curiosity and enjoyment that customers derive from their omnichannel service experience. To acquire customer knowledge, retailers may provide shopping-relevant incentives and technologies to motivate customers to provide suggestions on omnichannel retail offerings.

Second, omnichannel retailers should enhance the synergetic management of retailing technologies and channels in omnichannel integration to promote customer engagement. For informational integration, omnichannel retailers can rely on store salespeople and mobile apps to connect online and offline offerings. Emerging retailing technologies, such as text messages and digital coupon messages, should be managed to enhance the accessibility of omnichannel retailers' products and services. For transactional integration, omnichannel retailers should provide innovative payment technologies to synchronize online and offline customer payment experiences. Moreover, retailers can take the advantage of in-store pickup and cross-channel after-sales support technologies to satisfy customers' expectations. For relational integration, retailers can fully leverage the accumulation of omnichannel customer information to optimize the value propositions of their products and services. Additionally, shopping guide technologies in offline and online stores could be personalized to fit customers' individual preferences.

Third, we suggest that omnichannel retailers cultivate fluency and flow in the shopping experience in order to sustain customer engagement in technology-enabled omnichannel marketing. To cultivate fluency, retailers should implement and promote updated in-store technologies to assist customers visiting physical stores and generate enthusiasm about in-person visits. Retailers should also illustrate in detail the steps for using in-store pickup services in order to enhance customers' fluent and comprehensive understanding of the cross-channel shopping procedures. To facilitate the experience of flow, retailers should have an in-depth understanding of customer segments and provide personalized offerings that match customer interest. We also suggest retailers continuously improve their service procedures to establish an enjoyable omnichannel customer journey.

C. Limitations and Future Research

The limitations of this article provide opportunities for future research. First, the generalizability of research findings should be tested using omnichannel customers outside the MTurk sample. The MTurk sample offers several merits for survey-based and experimental research when a relatively large sample of omnichannel customers with diverse demographic backgrounds is needed. However, respondents' diverse demographic backgrounds pose challenges to analyzing the potential socioeconomic factors that may influence customers' channel preference in the omnichannel environment [79]. Future research should take a cross-cultural approach, collecting empirical data from different countries and regions in order to assess the influence of socioeconomic factors in omnichannel retailing. Meanwhile, although MTurk has made sampling much more convenient, it also receives its share of skepticism and controversy regarding the generalizability of research findings obtained using this platform [80]. We recommend that future researchers in this area cooperate with omnichannel retailers in order to collect survey data from real-world omnichannel customers.

Second, we identified 25 famous brands that provide omnichannel services, and this group can be broadly divided into the apparel and technology sectors. Although collecting data from customers of famous omnichannel brands enhances the representativeness of our data sample, it also poses a risk of low construct variance. Respondents with a high affinity for a particular omnichannel brand are inclined to give all aspects of the brand high scores, resulting in a lack of variance in constructs. Brand affinity, broadly defined as an individual's attraction to and interest in a particular brand, has been found to significantly influence customers' favorable perceptual responses toward the brand [98]. Future research may consider measuring the degree of brand affinity among respondents to distinguish the low and high conditions for ruling out the possibility that brand affinity may lead to low construct variance. Alternatively, researchers should recruit omnichannel customers from diverse brands in different sectors to enhance the variance of customers' perceptual data.

Third, omnichannel retailing evolves as new technologies emerge and thus requires future exploration of innovative business solutions in omnichannel retailing. Our article proposes three types of omnichannel integration and develops validated measures for omnichannel integration, which are highly relevant to the technology and channel management issues in omnichannel retailing. Additionally, we employed a recall method to activate customers' recent omnichannel shopping experiences, which serves as a basis for forming their perceptions of omnichannel integration. Although this recall method is a valid survey approach for collecting perceptual data by soliciting respondents' perceptions of prior experiences, future research should cross-validate the effects of omnichannel integration with experimental design to enhance the causality inferences among core variables in the research model.

Fourth, contrary to our expectations, informational integration has a nonsignificant effect on perceived flow. Although we offer a plausible explanation for this unexpected and surprising result, future research could seek more theoretical and empirical explanations. One possible direction is to examine the contingency factors that moderate the relationship between informational integration and perceived flow. For instance, a customer's digital information terminal (i.e., desk computer versus mobile phone) may serve as a potential boundary condition for the effect of informational integration on perceived flow. Prior studies have proposed that customers will more likely experience flow in searching and evaluating cross-channel shopping information when using their mobile phones compared to desk computers [99]. Future research should incorporate the type of digital information interface as a moderator to further validate the model.

VII. Conclusion

Omnichannel retailers face the challenge of synergetic management of cross-channel retail technologies to promote customer engagement and establish digital advantages over their competitors. Drawing upon S-D logic, we identify three types of omnichannel integration, namely, informational integration, transactional integration, and relational integration. We then develop a research model that accounts for the effect of omnichannel integration on customer engagement through formulating fluency and flow in the shopping experience. We believe that our findings serve as a basis for future inquiries into engineering and technology management in omnichannel retailing from the S-D logic perspective. Our findings also inspire managers to harness synergetic technology and channel management in omnichannel integration and provide actionable guidelines for designing effective omnichannel service systems to promote customer engagement.

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Yang Li received the Ph.D. degree in information systems at the joint Ph.D. program from the University of Science and Technology of China, Hefei, China and City University of Hong Kong, Hong Kong, in 2019.

She is currently a Lecturer of management science and engineering with the Management School, Hefei University of Technology, Hefei, China. She has authored/coauthored academic journals, including *Decision Support Systems*, *Internet Research*, *Information and Management*. Her research interests include omnichannel management, supply chain management, and e-commerce.

Xiang Gong received the Ph.D. degree in information systems at the joint Ph.D. program from the University of Science and Technology of China, Hefei, China and City University of Hong Kong, Hong Kong, in 2019.

He is currently an Associate Professor of marketing with the Management School, Xi'an Jiaotong University, Xi'an, China. He has authored/coauthored international journals, including *Journal of the Association for Information Systems*, *Information Systems Journal*, and *Information and Management*. His research interests include cyberdeviance, sharing economy, and social commerce.