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Research paper

Mobile targeting in industrial marketing: Connecting with the right businesses

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ABSTRACT

Although the existing literature has acknowledged the importance of mobile marketing, few scholars have examined the efficacy of mobile targeting. This paper contributes to the burgeoning literature on mobile targeting by investigating the effects of customer mobile habits and social capital on firm sales. Leveraging unique customer mobile browsing data from a major telecom service provider in China, we use a Bayesian SEM (structural equation modeling) approach to show that customer mobile habits and social capital exert significant influences on customers' purchase intentions. Specifically, customers who engage in more hedonic mobile behaviors, such as social networking, video browsing, and gaming are associated with a higher probability of purchasing, controlling for the usage of communications apps including messaging and emailing apps, and the usage of functional apps, such as maps, living services, and app market apps. Additionally, our research results reveal a significant positive effect of social capital on firms' sales performance. These findings offer important insights that are often missing from organizational targeting campaign designs in terms of targeting both the right customers and the right business alliance partners and enable a better understanding of managerial and decision-making implications in the context of the B2B market in general.

1. Introduction

The emergence of big data has provided new opportunities for firms to improve their business performance by tracking customer behaviors and uncovering important patterns of their customers (Y. Lee, Madnick, Wang, Wang, & Zhang, 2014; Y. Wang, Kung, Wang, & Cegielski, 2018). In today's internet age, customers are generating a large amount of data online, which enables firms to analyze their featured data and support their marketing promotion strategies (Erevelles, Fukawa, & Swayne, 2016; Salehan & Kim, 2016; Y. Wang & Hajli, 2017). As such, consumer-generated big data play an important role for firms in gaining knowledge about their customers and businesses; thus, the application of big data analytics to business practices is critical for industries and firms to gain competitive advantages and improve their performance.

However, gathering big data usually appears to be treated as an end in itself since much of the collected data have not been properly managed or analyzed for specific marketing purposes. Such inefficient use of big data is due to different managerial and technical reasons, ranging from a lack of understanding of the importance of big data analytics, to insufficient data analysis skills or knowledge (Khalilzadeh & Tasci, 2017). Especially in the B2B market, the economic weight (in terms of total transaction value) of which is similar to that of the B2C market, big data analytics have received much less academic attention than we would expect (Wiersema, 2013). Nevertheless, as companies now have increasing access to big data, it enables us to look more closely at consumers and business partners than we previously could. Players in B2B markets start to shift their attention away from the historical key aspects of the B2B marketplace (e.g., products and supplier technology) to customer-facing functions (Lilien, 2016), particularly by leveraging emerging big data resources such as *mobile big data,* which allow us to track customer behavior without location and time constraints (Chung, Rust, & Wedel, 2009; Luo, Andrews, Fang, & Phang, 2013).

As smartphone usage, app adoption, and mobile browsing continue to soar, firms are increasingly harnessing the power of mobile channels to boost sales. The previous research has demonstrated the substantial implications of mobile marketing in B2C markets for promotion performance (Hui, Inman, Huang, & Suher, 2013), consumer targeting

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(Luo et al., 2013), advertising effectiveness (Bart, Stephen, & Sarvary, 2014), consumer information searches (Xu, Forman, Kim, & Van Ittersum, 2014), and competitive strategies (Xu et al., 2014). These implications, though not equivalent to those in B2B markets, may still hold vacuously in B2B markets, particularly when mobile apps[1] enable companies to connect and interact with and track the operational behavior of other individual industrial users. Indeed, mobile apps not only offer the inherent potential for firms to collect individual consumer information but also allow industrial players to obtain organizational inputs such as pre- and post-sales information, underlying value-adding opportunities in big data analytics, and predictive operational support.

Mobile targeting refers to the usage of mobile data as an alternative source to manage marketing strategies, which enables marketers to simultaneously employ geographical and temporal targeting strategies (Luo et al., 2013). Mobile targeting in B2B markets involves connecting with the right business partners and, eventually, profitable consumers. In addition, effective mobile targeting strategies have the potential to lead to strategic alliances, which have many implications, in particular, (1) a marketplace signal in which the business partner can successfully signal information that the focal business could not itself signal (Akdeniz, Calantone, & Voorhees, 2013; Gammoh, Voss, & Chakraborty, 2006) and (2) social capital, which appears as a result of collaboration and interaction among business partners (Carmona-Lavado, Cuevas-Rodríguez, & Cabello-Medina, 2010).

However, in reality, the relationships both between firms and consumers are dynamic and thus unpredictable (Gupta, Foroudi, & Yen, 2018). Consequently, connecting to the right business partners and the right customer base becomes essential for firms to sustain profitability. Some apps that aim to address such concerns in B2B markets have already gained great popularity, including Salesforce Mobile, HootSuite, and DocuSign. These apps allow firms to manage their sales-forces, social media accounts, and customer relationships in general. The data related to the apps allow for a better understanding of business partners and customers (Müller, Pommeranz, Weisser, & Voigt, 2018) and enable the identification of effective targeting strategies, which eventually lead to a new type of organizational capability. To provide an enhanced understanding of mobile marketing, we seek to leverage big data analytics and uncover the trends in consumers' decision making, thus informing business practices.

As such, we analyzed an individual-level customer mobile dataset from a major telecom service provider in China. This unique dataset is merged from three data sources: conventional wireless communication data (e.g., calls and texts), mobile application data (e.g., apps), and customer demographic data. The wireless communication data allow us to derive an ego's social capital based on a calling network (e.g., network entropy) and expenditures on communication services (e.g., phone price and monthly service fee). The mobile app data enable us to construct customers' major mobile behaviors, including communication behaviors, hedonic habits, and functional behaviors. Employing the Bayesian structural equation model (SEM), we uncover the effects of customers' social capital and different mobile behaviors on their shopping behavior.

Our work provides novel theoretical insights by using mobile data to capture shopping behaviors and their relationship with hedonic values and social capital. This work can potentially make three primary contributions. First, our study advances the literature on mobile targeting by demonstrating how it can be used as an approach by companies to more accurately and effectively target customers and increase sales. In particular, our results suggest that only mobile hedonic behaviors can significantly improve customer shopping frequency, although customers engage in various mobile behaviors including communication, functional, and hedonic behaviors. As such, the hedonic habits of consumers, evaluated based on their mobile behaviors provide accurate and valuable references for marketers to consider in mobile targeting. Therefore, this work advances our understanding by extending the use of mobile targeting in marketing. Second, our study provides an alternative and relatively unbiased measurement of social capital based on customers' telecommunication connection and behavior data and shows that the use of mobile data to target customers that are high in social capital can be more efficient in improving firms' sales. The proposed measurement of social capital has the advantage of immediacy and cost effectiveness compared to the conventional measurements obtained from surveys or questionnaires, which involve substantial monetary investment and usually lag behind sudden market changes. Finally, our study provides some insights into the synergy between customers' social capital and hedonic habits. By mobile targeting customers that are high in both hedonic values and social capital, companies can be more effective (i.e., correct targeting) and efficient (i.e., cost-saving) in improving their sales. This finding also complements the theory of customers' social capital and hedonic values by bridging them together under an integrated framework.

Our findings also offer important managerial and marketing implications that are often missing in the context of the B2B market. Specifically, our work provides practitioners with an enhanced understanding of the application of mobile big data by combining independent data sources across different business departments within an organization. In our study, social capital is constructed from wireless communication data, while customer hedonic value is extracted from mobile application data. The fusion of these two isolated data sources enables us to simultaneously analyze the two key constructs in an integrated empirical framework. Additionally, our work demonstrates that the Bayesian SEM approach can effectively deal with a high dimensional data structure in business. Given that we were able to summarize 16 observed proxies (observed telecommunication behavior and app behavior) into 5 meaningful latent variables (social capital, communication behavior, hedonic habits, functional behavior, and shopping behavior), our paper showcases the applicability of Bayesian SEM in the dimension reduction of complicated business data. Finally, our study extends mobile targeting to the context of B2B markets by showing that strategic alliances based on customers' social capital can improve partner firms' sales performance. In particular, a focal firm can potentially boost its sales by targeting customers who are also customers of the ally firm. Consequently, a business partner can exploit a stronger positive effect of social capital (on sales) than that it can achieve on its own.

The remainder of this paper is organized as follows. First, it presents the literature on the key concepts, leading to the development of hypotheses. Second, it details the big data collection, analysis, and research findings. Third, it contains a discussion of the theoretical and practical implications.

2. Key concepts and hypothesis development

In this section, the key concepts from big data analytics are presented, and hypotheses are proposed.

2.1. Customer hedonic value, mobile targeting, and firm sales performance

Mobile targeting can increase consumer-perceived playfulness in online shopping, which influences consumers' perceptions and purchase intentions. The hedonic value of shopping reflects the values that consumers receive from the multisensory, fantastic, and emotive aspects of their shopping experiences, such as entertainment and pleasure (Hirschman & Holbrook, 1982; Jones, Reynolds, & Arnold, 2006). With a mobile targeting feature, consumers can access more channels for similar products and services, which can usually lead to more informed decision making and better deals. In such a scenario, consumers feel happy and experience pleasure as a result of these more accurate

[1] Apps are software programs, such as a video player or a shopping program that allows people to purchase online, used on mobile phones.

purchase decisions.

The previous literature has demonstrated that hedonic value positively affects online shopping, including satisfaction, purchase intentions, and repurchase intentions (Chiu, Wang, Fang, & Huang, 2014; Overby & Lee, 2006). It is even easier for firms and customers to have habitual interactions in the context of mobile targeting than in conventional online scenarios because the mobile devices themselves are an integral part of customers' daily routines (R. J.-H. Wang, Malthouse, & Krishnamurthi, 2015). The nature of mobile phones, such as their portability, multifunctionality, and proximity to owners, provides firms with automatic, unobtrusive and continuous measures of customers' hedonic interests and habits (Jia, Jia, Hsee, & Shiv, 2017). As customers become dependent on their hedonic habits, they rely on automatic thinking and cease to consider alternatives (Fazio, Ledbetter, & Towles-Schwen, 2000). As such, firms can gain more opportunities to interact with customers, thus enhancing their relationships with customers and increasing customers' purchase intentions. All these factors can eventually lead to increased purchasing frequency and quantity. We therefore posit the following hypothesis:

Hypothesis 1. Consumers' hedonic value positively affects firms' sales through mobile targeting.

2.2. *Social capital, mobile targeting, and firm Sale performance*

Social capital is defined as "the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit" (Nahapiet & Ghoshal, 1998, p. 243). Coleman (1990) identified two characteristics of social capital: (1) it constitutes some aspect of the social structure and (2) it facilitates the actions of individuals within the structure. Therefore, social capital includes resources such as the network, the people, and the relationships developed through the network. Mobile targeting enables consumers to expand social capital resources by exploring multiple mobile channels to acquire products and services. In addition, Carmona-Lavado et al. (2010) suggested that social capital is a resource generated by the interpersonal or interorganizational networks embedded and available within it.

The extant literature has documented a positive relationship between social capital and firm sales performance (Lin, Prabhala, & Viswanathan, 2013; Moran, 2005). Primarily from an administrative perspective, the previous research has focused on the social capital of either the management or frontline workforces and argued that organizational social capital can increase a firm's sales performance by enhancing commitment, increasing flexibility, and fostering intellectual capital (Shaw, Duffy, Johnson, & Lockhart, 2005). In the context of mobile targeting, we argue that social capital is an asset that is constructed not only by the company itself but also jointly by its customers. Customers with higher social capital usually have larger needs for social interaction, recognition, and intimate relationships (Adler & Kwon, 2002; Bubolz, 2001). As mobile devices enable firms to communicate with customers without temporal and spatial constraints, mobile targeting is sufficiently flexible in providing convenient access when customers want to achieve specific goals or fulfill their needs that require direct attention or cognition. Such mobile convenience reinforces customers' experiences of being in a relationship with a firm and then leads to behavioral loyalty, enhanced purchase intentions, and repeated purchases. Additionally, from a network perspective, greater social capital implies larger customer networks that are affiliated with a focal customer. The mobile targeting of a focal customer will motivate him/her to consider the purchasing needs of the customers that he/she is affiliated with (e.g., a university student with more friends is likely to buy more food and drinks upon his/her friends' visits) and thus increase his/her purchase intention. We therefore hypothesize the following:

Hypothesis 2. Consumers' social capital positively affects firms' sales through mobile targeting.

2.3. *Synergy between customer hedonic value and social capital in mobile targeting*

The foregoing discussion demonstrates that in the context of mobile targeting, both customer hedonic value and social capital can reinforce customers' mobile shopping behaviors. While customer hedonic value is a pleasure-induced reliance on habitual behaviors on mobile phones, social capital originates from the satisfaction of the fulfillment of needs through intensive and timely communications using mobile phones. Seemingly separate, the effects of customer hedonic value and social capital (on sales) can be interdependent. Although customers' hedonic parameters are usually assumed to be stable across business scenarios (Hellén & Sääksjärvi, 2011; Koschat & Putsis Jr, 2002), customers' hedonic value for a focal company can change when they encounter external cues (López & De Maya, 2012). For example, when customers encounter competing firms' mobile targeting, their reliance on hedonic habits toward the focal firm will be weakened, which in turn will decrease their purchasing frequency.

Opportunely, customers' social capital can serve as an internal cue that protects customers from negative external cues. Compared to customers with low social capital, those with high social capital enjoy anytime-anywhere convenience and additional touch-point opportunities introduced by mobile targeting. As they are deeply engaged with and are a stable and loyal customer of the focal company, they are less susceptible to the weakening effect of customer hedonic value (on firm sales) due to negative external cues. We therefore argue that with a higher level of social capital, the impact of customers' hedonic value on their mobile shopping behavior will be stronger.

Hypothesis 3. Consumers social capital increases the positive effect of hedonic value on firms sales through mobile targeting.

3. Data and analyses

3.1. *Data description*

We collaborated with one of the major mobile service providers in China and obtained fruitful demographic and mobile-phone data of customers for this study.

The first part of the data concerns the usage of mobile-phone applications (apps). These data were utilized as proxies for capturing the different kinds of interests and activities of customers. Over 90 of the most popular mobile apps were examined in this study, which were precategorized by the mobile service provider into several subcategories (see Table 1 for the individual apps in each subcategories): shopping, video, music, social networking, games, instant messaging, multimedia messaging (e.g., internet-based text messaging), maps and GPS, living services (e.g., weather and travel), tools, and app markets (i.e., for downloading apps). The usage of apps in each subcategory (see Tables 1–2) was summed to reflect a customer's overall use frequency of such kinds of apps. The usage of shopping apps measures customers' mobile shopping behavior and indicate customers' interest in shopping online. We utilize customers' mobile shopping behavior (as measured by the usage of shopping apps including "Taobao" and "Alipay"[2]) as a proxy for a firm's sales performance, which is the major dependent variable in this analysis. There are two main reasons for this operationalization: first, the extant literature has established that customers' purchases through mobile channels overall increase firm sales, even

[2] The shopping apps that we consider in the analysis include "Taobao" and "Alipay", which are two major shopping apps provided by the largest Chinese e-commerce platform, "Taobao Website". The promotional event organized by the platform ('Double 11') will be introduced in later sections.

through mobile targeting.

Table 1
Categories of mobile phone apps.

Category	Apps
Shopping behavior	
Taobao (1 app)	
Alipay (1 app)	
Hedonic behavior	
Video (18 apps)	UC_video, Letv, Mobile_TV(Dopool), Fantastic_Art Film, Tencent_Video, Thunderstorm_Video, No.1_Movies_Net, Kankan, National Telecine, Mobile_Thunder, PPStream_Mobile_version, Kankan_Mobile, Panda_Video91, Phoenix_Video, Chihiro_Television, Mobile_Youku_online, Mobile_Tudou
Music (7 apps)	Mobile_Google_Music, Love_Music, Everyday_Sounds, Meters_Music, QQ_Mobile_Music, Kugou Music, I_Listen
Social networking (8 apps)	QQ_space, Renren, Kaixin_web, Mobile_Tianya, Jiayuan, Sohu_Weibo, Sina_Weibo, Tencent_Weibo
Game (21 apps)	Three_Kingdom_OL, Three_Kingdom_Reggie_OL, Elder_2, World_OL, Kyushu_OL, Farm91, Loyalty_OL, Flush_Phone, Pearl_of_the_Three_Kingdoms, Tamrac_OL, Martial_Arts_OL, Drift_Bottles, Qianlong_OL, QQ_Landlords, QQ_Game_Hall, Three_Kingdom_Killed_OL, Tragedy_OL, Heaven_OL, Jermaine_O'Neal_Game_City, Kingdom_OL, Love_Game
Communication behavior	
Instant messaging (7 apps)	Wechat, Mobile_QQ, YY_vioce, Mobile_MSN, G_talk, Miliao, Yixin
Multimedia messaging (4 apps)	WAP_MMS, HTTP_MMS, Youni_SMS, Fesion
Email (3 apps)	QQ_mail, ShangMail, Email189
Functional behavior	
Map and GPS (6 apps)	Baidu_Maps, Google_Maps, Stock_map, GPS_positioning, AutoNavi_Map, Abc_map
Living services (6 apps)	Ink_weather, I_Check, Love_city, Flight_Steward, Go_to_the_market_life, Ctrip, Dindin_Life
Tools (5 apps)	Sogou_input_method, Baidu_input_method, Mobile_Guards360, Mobile_Assistant91, lflytek_input
App market (5 apps)	Android_Market, ING_Market, China_Appindex, AppChina, Tianyi_Space

though the purchases on the web channel can be slightly cannibalized (R. J.-H. Wang et al., 2015). In addition, Cao and Li (2015) suggest that even for conventional offline retailers, mobile channels serve as an integral part of firms' selling channels and positively contribute to retailers' sales growth. Second, it has been highlighted in the literature that mobile phone data not only are in vitro reflections of mobile phone-based activities but also reflect individuals' general psychological interests (Eagle, Pentland, & Lazer, 2009; Jia et al., 2017; Saramäki et al., 2014). For example, frequent mobile purchases reflect a customer's general interest in shopping behavior and thus signal the probability that he/she will contribute to a company's sales.

According to the use and purpose of apps, we categorized the remaining apps into three major categories hedonic, communications, and functional apps which are proxies to measure customers' hedonic, communication, and functional behaviors or interests. In principle, any app that is intended for leisure, diversion, or enjoyment, is categorized into the hedonic category; any app that is intended for interpersonal communications is categorized into the communications category; and any app that has a utilitarian role in customers' daily life is categorized into the functional category.

As an individual's relative usage of different mobile apps precisely reflects his or her general psychological interests, the usage of hedonic apps captures customers' hedonic values, which is one of the key explanatory variables in our empirical model. The other two categories of mobile apps reflect the other two major activities of customers on their mobile phone, i.e., communication activities and functional activities (Jia et al., 2017). To precisely identify the relationship between customers' hedonic habits and their shopping behavior, we explicitly control for customers' communication and functional behaviors as measured by their usage of communication apps and functional apps, respectively.

The second part of the data is users' wireless behavior data, including each user's phone price, phone bills, voice calls, texts, internet usage, and network centrality. In contrast to the app data, the wireless telecommunications data do not disclose customers' general psychological interests but allow us to depict customers' social capital. In detail, this part of the data contains the price of the cellular device used by a customer; ARPU (average revenue per user), a measure of the revenue generated by one customer's cellular device from his/her overall phone bill; daily voice calls made by a customer; daily short text messages sent

Table 2
Summary statistics in the final mobile phone data set (n = 17,398).

Variable	Definition	Mean	Median	Std. Dev.	Min	Max
Tabao app	Frequency on Nov. 11, 2013	4.03	0.00	14.90	0.00	241.00
Alipay app	Frequency on Nov. 11, 2013	5.25	0.00	13.10	0.00	375.00
Video apps	Average frequency during Nov. 4–10, 2013	8.72	2.00	18.44	0.00	257.28
Music apps	Average frequency during Nov. 4–10, 2013	3.10	2.86	7.84	0.00	172.57
Social networking apps	Average frequency during Nov. 4–10, 2013	14.09	4.00	26.08	0.00	457.57
Game apps	Average frequency during Nov. 4–10, 2013	6.55	1.14	8.52	0.00	91.57
Instant messaging apps	Average frequency during Nov. 4–10, 2013	135.08	77.29	151.87	0.00	1050.71
Multimedia messaging apps	Average frequency during Nov. 4–10, 2013	2.68	0.00	9.43	0.00	278.28
Email apps	Average frequency during Nov. 4–10, 2013	5.45	2.86	18.78	0.00	409.71
Map and GPS apps	Average frequency during Nov. 4–10, 2013	8.82	2.00	15.32	0.00	228.57
Living services apps	Average frequency during Nov. 4–10, 2013	7.76	0.00	2.79	0.00	58.71
Tools apps	Average frequency during Nov. 4–10, 2013	10.37	0.57	27.39	0.00	401.43
App market apps	Average frequency during Nov. 4–10, 2013	2.40	0.00	7.87	0.00	165.28
ARPU	Average revenue per mobile user during Nov. 4–10, 2013	73.6	53.02	81.29	0.00	1350.87
Calls	Average daily voice calls during Nov. 4–10, 2013	4.81	3.86	3.30	1.00	76.00
Texts	Average texts in Nov. 4–10, 2013	0.79	0.43	1.34	0.00	67.00
GPRS	Average daily internet usage during Nov. 4–10, 2013	15.48	8.48	27.65	0.00	1028.82
Price	Price of cellular device	1750.94	1090.00	1349.38	0.00	9580.00
Age	Age	36.67	36.00	10.65	15.00	95.00
Gender	Male = 1, Female = 0	0.66	1.00	0.47	0.00	1.00

by a customer; GPRS (general packet radio service), a measure of the daily internet usage of a customer from the wireless service provider; and a daily measure of network centrality, i.e., entropy, of a customer, which is calculated by the mobile service provider based on the calling network of the customer. Per the discussion with the manager of the mobile service provider, we applied ARPU, entropy, and phone price, indicators of both the network centrality and personal wealth of a customer, as proxies to measure his/her social capital. Daily voice calls, short messages, and internet usage serve as controls of customers' wireless habits. These controls help to control for alternate explanations due to customers' wireless habits. For example, it is possible that users with higher data usage are more likely to shop online using their mobile phones because they tend to be familiar with such an operation (Luo et al., 2013).

The final part of the data is users' demographic information including their age and gender. Because of strict regulations in the wireless industry, customers' private information is not trivial to obtain (Luo et al., 2013). However, personal characteristics have been widely recognized as important factors in explaining subjects' different kinds of behavior. For example, females may tend to react more to promotional events and thus shop more on their mobile phone than males. The age and gender of customers are applied as controls in the statistical modeling to obtain more validated results.

In this study, we set out to evaluate whether the daily behavior (especially for the hedonic habits) and social capital of customers can be used to predict their shopping behavior. We obtained the mobile phone data for eight days, including the day of the famous event, "Double 11", of Nov. 11, 2013, and a week before that day. The "Double 11" event was started in 2009 by "Taobao Website", the largest Chinese e-commerce platform, and has become the major promotional event in China. On Nov11, 2013, the "Taobao" platform was able to obtain daily sales of 35 billion RMB (approximately 5 billion U.S. dollars).[3] We measured customers' shopping behavior using their shopping app usage on Nov. 11, 2013. Even though the use of daily data has potential limitations compared to the use of longitudinal data, it has two major advantages in using the daily usage of apps (on the day of the "Double 11" event) as the measure of shopping behavior and firms' sales. On the one hand, the "Double 11" event is the most important and major online event in China, and the involved customers are abundant and representative of the online population in general. On the other hand, the daily shopping data for Nov. 11 is particularly strongly connected to real firm sales and is usually considered an industrial benchmark for predicting and evaluating firms' sales performance. To avoid the substantial influence of the "Double 11" event on the measures of customers' daily behavior and their social capital,[4] we applied the daily average values of the data from the week before the promotional event to precisely measure customers' daily behavior and social capital. After the combination of the three mentioned sources of data for eight days, a total of 17,398 mobile phone users (2.95% of all customers of the provider in that city) with over 20 million entries of mobile phone app usage records from a medium-sized city in western China were included in the final dataset. The summary statistics of the variables in our data set are depicted in Table 2.

[3] Data source 'http://tech.ifeng.com/a/20171111/44755945_0.shtml?_zbs_baidu_bk'

[4] At the day of the large promotional event, customers may exhibit very different app usage and telecommunications patterns, which are naturally correlated with their shopping behavior due to the promotional event. However, the aim of this analysis is to reveal whether the average daily behavior patterns and social capital of customers can be used to predict their shopping behavior. We therefore used the data of the week before the "Double 11" event to measure the daily behavior patterns and social capital of customers. The obtained results are beneficial for companies to target their clients or to seek business partners that have customers with such behavior patterns.

3.2. Methodology overview

In the section on hypothesis development, we discussed customers' theoretical attributes, such as their hedonic habits and social capital, which may influence their shopping behavior, especially their impulsive reactions to promotional events. People's hedonic habits and social capital are complicated latent variables that cannot be assessed through a single manifest variable. For instance, a customer may exhibit broad hedonic habits such as listening to music and watching movies, and a customer's social capital can be reflected by his/her expense level and social connections. Thus, multiple correlated indicators that reflect people's hedonic habits and social capital from different perspectives should be utilized to formulate the latent constructs; a careful treatment of the manifest variables and a rigorous formation of the latent variables are necessary.

Unfortunately, the developed theories do not provide us with the exact relationships among the latent constructs and between the latent variables and their proxies. The linear regression model using the basic ordinary least squares (OLS) approach has been used in previous empirical studies to analyze the relationships using proxies for the unobservable theoretical constructs. However, there might be problems in such applications, such as multicollinearity among the correlated manifest variables. In addition, Titman and Wessels (1988) highlight further problems. First, the simple linear regression analysis ignores the measurement errors of imperfect manifest variables for the latent constructs, which may lead to an errors-in-variables problem. Second, the lack of unique representation of the latent constructs may lead researchers to choose variables solely based on statistical criteria and neglect the economic interpretation. To tackle these potential problems, we utilized Bayesian structural equation modeling (SEM) to formulate the latent constructs and to conduct the statistical analysis.

In general, SEM comprises two components, a measurement equation that characterizes latent constructs through multiple correlated manifest variables using a confirmatory factor analysis model and a structural equation that assesses the interrelationships among latent variables through regression models. By grouping multiple correlated manifest variables into a few less correlated latent variables, the SEM technique not only alleviates the multicollinearity problem potentially induced by the correlation but also significantly reduces the model dimensionality, thereby providing attractive interpretation ability for the analysis.

Bayesian SEM is an advanced methodology that enjoys wide attention from both the methodological and empirical literature (see Assaf, Tsionas, & Oh, 2018; S.-Y. Lee & Song, 2012). A sampling-based Bayesian technique outperforms the traditional frequentist method in SEM in the following ways. First, it utilizes authentic prior information to achieve better estimations and convergence. Second, it does not rely on the large-sample asymptotic theory and thereby produces more reliable estimations, even with relatively small sample sizes. Finally, with the aid of the rapid development of modern statistical computing methods, the Bayesian technique makes it feasible to conduct complex analyses that concern multiple latent variables.

3.3. Main analysis using Bayesian SEM

The Bayesian SEM methodology is described as follows. Let $\mathbf{y_i} = (y_{i1}, \ldots, y_{ip})'$ be the ith $p \times 1$vector of the manifest variables (proxies for latent variables) in the sample of size $n = 17398$, $p = 16$; $\boldsymbol{\omega_i} = (\omega_{i1}, \ldots, \omega_{iq})'$be the $q \times 1$ vector of the latent variables of interest that are formulated based on $\mathbf{y_i}$; and $q = 5$. The measurement equation of SEM can be expressed as the following factor analysis model:

$$\boldsymbol{y_i} = \boldsymbol{\mu} + \boldsymbol{\Lambda}\boldsymbol{\omega_i} + \epsilon_i,\ i = 1,\ \ldots, n, \tag{1}$$

where $\boldsymbol{\mu}$ is the $p \times 1$ vector of the intercept, $\boldsymbol{\Lambda}$ is a $p \times q$ matrix of factor loadings, and ϵ_i is a $p \times 1$ vector of random errors, independent of $\boldsymbol{\omega_i}$ and distributed as a multivariate normal distribution $\mathbf{N}(\mathbf{0}, \Psi)$ with a

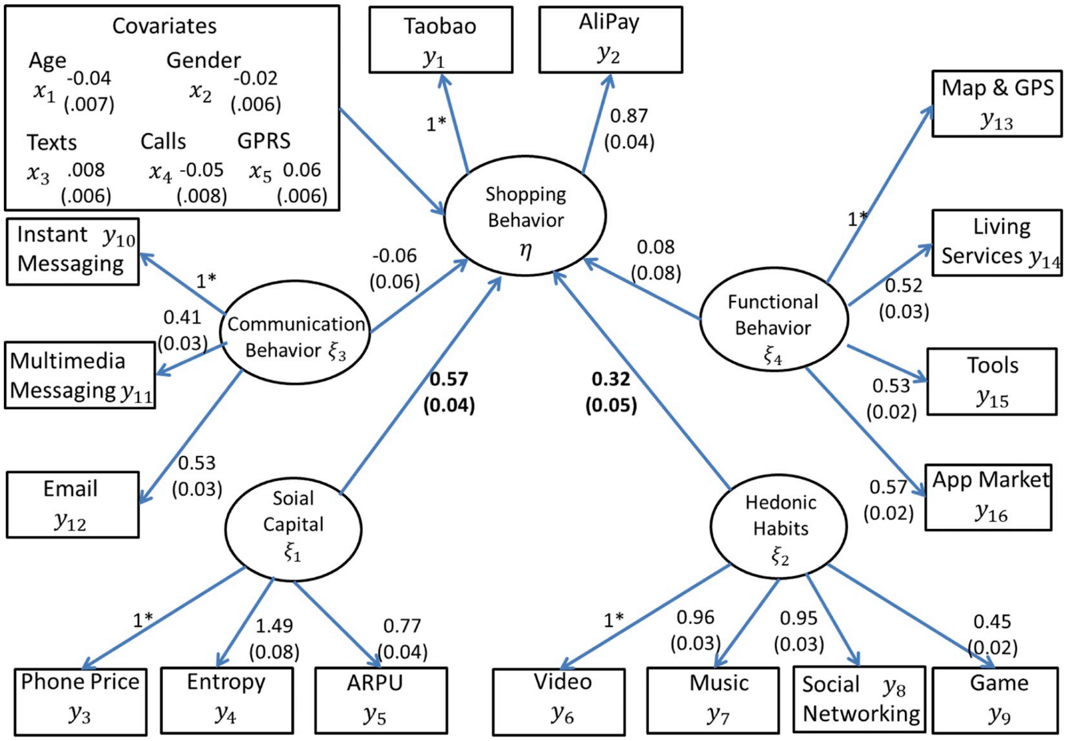

Fig. 1. The path diagram of SEM in the main analysis. The estimates of the factor loadings in the measurement equation and coefficients in the structural equation, together with their standard errors (in parentheses), are given next to the paths.

diagonal covariance matrix Ψ.

In the structural equation, $\boldsymbol{\omega}_i$ is further partitioned into $(\eta_i, \xi_{i1}, \xi_{i2}, \xi_{i3}, \xi_{i4})'$, where η is the outcome latent variable that measures customers' shopping behavior and ξs are explanatory latent variables that measure customers' social capital (ξ_{i1}), hedonic habits (ξ_{i2}), communication behavior (ξ_{i3}), and functions behavior (ξ_{i4}) and are distributed as $\mathbf{N}(\mathbf{0}, \boldsymbol{\Phi})$. The influential effects of the explanatory latent variables on the outcome latent variable are examined through the following regression equations (**Model I**):

$$\eta_i = \sum_{j=1}^{5} b_j x_{ij} + \sum_{j=1}^{4} \gamma_j \xi_{ij} + \delta_i, \tag{2}$$

where xs are control variables such as the age, gender, average daily SMS usage, average daily voice call frequency, and average daily data usage volume of each subject; bs and γs are unknown coefficients; and δ_i is the random error distributed as $N(0, \sigma)$. We demonstrate the relationships among the latent variables and between the latent variables and their manifest variables through a path diagram in Fig. 1.

It is known that the SEM defined by Eq. (1) and Eq. (2) is not statistically identifiable without imposing further identification conditions (Feng, Wu, & Song, 2017; S.-Y. Lee & Song, 2012). We followed the common practice in the literature to fix certain factor loadings in $\boldsymbol{\Lambda}$ at preassigned values, which can be decided through the associations between latent variables and their respective manifest variables. As discussed in the data description section, the associations between the latent variables and their manifest variables are clear and are represented through the following nonoverlapping structure of $\boldsymbol{\Lambda}$:

1	λ_{12}	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	λ_{24}	λ_{25}	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	λ_{37}	λ_{38}	λ_{39}	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	$\lambda_{4,\,11}$	$\lambda_{4,\,12}$	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	$\lambda_{5,\,14}$	$\lambda_{5,\,15}$	$\lambda_{5,\,16}$

The fixed 0 and 1 are preassigned values for identifying the model and introduce a scale to each latent variable. The nonoverlapping structure not only statistically identifies the model but also ensures that each latent variable has a clear interpretation.

The Bayesian method suggested by (S.-Y. Lee & Song, 2012) was utilized in the current study to conduct statistical inference on the proposed model. As previously discussed, the sampling-based Bayesian approach enjoys many appealing features, yet it requires tedious derivation of the posterior distributions for the unknown parameters. Fortunately, there are well-developed Bayesian inference software, such as WinBUGS (D. Spiegelhalter, Thomas, Best, & Lunn, 2003) and R2WinBUGS (Sturtz, Ligges, & Gelman, 2005), helping to decrease the burden of the technical derivation of the posteriors.

The inference procedures are briefly elaborated as follows:

Step 1. Conjugate prior distributions together with predefined hyperparameters were assigned to the unknown parameters. The hyperparameters are defined to reflect our prior knowledge of the unknown parameters. In this study, we had minor knowledge of the true values of the unknown parameters, and thus used noninformative priors with large variances for the unknown parameters.

Step 2. Based on the data inputs, the model specifications of Eqs. (1) and (2), and the specified prior distributions, the WinBUGS software automatically derives the conditional posterior distributions for the unknown parameters. Based on the conditionals, the Markov chain Monte Carlo posterior samples were iteratively generated.

Step 3. The algorithm was found to converge within 10,000 iterations based on the traceplots of two chains with very different initial values. We thus collected 10,000 posterior samples after the burn-in phase of 10,000 iterations. The posterior distributions of the unknown parameters can be described through the samples, and we calculated the posterior means and corresponding standard errors of the parameters.

The goodness of fit of the model was evaluated using well-known Bayesian model-checking statistics, the posterior predictive (PP) *p*-value, which measures the discrepancy between the data and the selected model (Gelman, Meng, & Stern, 1996; Meng, 1994). Classical tests including the χ^2test and goodness-of-fit indices in existing software are not applicable due to the complexity of the current Baeysain SEM approach. (Meng, 1994) stated that a PP *p*-value of approximately 0.5 indicates a reasonable model fit. In this analysis, the PP *p*-value was calculated to be 0.486, suggesting a plausible fit of the proposed model to the data. We refer readers to (S.-Y. Lee & Song, 2012) for the detailed implementation of the statistical inference of Bayesian SEM. The estimation results of the important parameters are given in Fig. 1, which can be explained as follows.

For the factor analysis model, all the factor loadings were estimated to be significantly deviant from 0 and larger than 0.3 (S.-Y. Lee, 2007), confirming the close associations between the latent constructs and their manifest variables. Based on the meaning of each manifest variable and its corresponding factor loading estimation, the following interpretations for the latent variables can be obtained: (i) a higher score for 'shopping behavior (η)' shows that the customer shops online using his/her mobile phone more frequently; (ii) a higher score for 'social capital (ξ_1)' indicates that the customer has more resources and social connections; (iii) a higher score for 'hedonic behavior (ξ_2)' shows that the customer engages more in hedonic activities on his/her mobile phone; (iv) a higher score for 'communication behavior (ξ_3)' denotes that the customer communicates with others more frequently using his/her mobile phone. (v) a higher score for 'functional behavior (ξ_4)' shows that the customer uses functional apps more often on his/her mobile phone.

The structural equation evaluates the effects of the explanatory latent variables on the interested outcome latent variable, customers' shopping behavior on their mobile phones. Based on the interpretations of the latent variables and the detected significant effects in the structural equation, the interrelationships among the latent variables are described as follows. (i) Hedonic behavior (ξ_2) is a highly significantly positive influential factor ($\gamma_2 = 0.32$) of customers' shopping behavior. People who engage more in hedonic activities on their mobile phone tend to shop more frequently on their mobile phones. This result provides support for the developed hypothesis H1. (ii) Social capital (ξ_1) is another substantial positive predictor ($\gamma_1 = 0.57$) of customers' shopping behavior, which reflects that customers with higher social capital tend to shop more on their mobile phones than do those with lower social capital. The developed hypothesis H2 is thus supported. (iii) The structural equation also controls for customers' communication (ξ_3) and functional (ξ_4) behaviors on their mobile phones and the corresponding effects ($\gamma_3 = -0.06$, $\gamma_4 = 0.08$) are negligible.

3.4. Alternative models and robustness check

The above analysis provides initial evidence that the social capital and hedonic habits of customers are crucial factors in explaining their shopping behavior. Further analyses are needed to confirm that these factors are truly important predictors of customers' shopping behavior. To provide further evidence for the main analysis, we considered the following alternative model for Model I in the main analysis.

Model II (Removing social capital from the structural equation, a further test for H1):

$$\eta_i = \sum_{j=1}^{5} b_j x_{ij} + \gamma_2 \xi_{i2} + \gamma_3 \xi_{i3} + \gamma_4 \xi_{i4} + \delta_i. \tag{3}$$

Model III (Removing hedonic habits, a further test for H2):

$$\eta_i = \sum_{j=1}^{5} b_j x_{ij} + \gamma_1 \xi_{i1} + \gamma_3 \xi_{i3} + \gamma_4 \xi_{i4} + \delta_i. \tag{4}$$

Model IV (Removing social capital and hedonic habits, a further test for H1 and H2):

$$\eta_i = \sum_{j=1}^{5} b_j x_{ij} + \gamma_3 \xi_{i3} + \gamma_4 \xi_{i4} + \delta_i. \tag{5}$$

Model V (Removing communication and functional behaviors, a placebo test):

$$\eta_i = \sum_{j=1}^{5} b_j x_{ij} + \gamma_3 \xi_{i3} + \gamma_4 \xi_{i4} + \delta_i. \tag{6}$$

The factor analysis model for the five candidate models was maintained the same way for a fair comparison. Of the candidate models, the best-performing one from a statistical point of view was selected using a widely applied Bayesian model comparison statistic, the deviance information criterion (DIC; D. J. Spiegelhalter, Best, Carlin, & Van Der Linde, 2002). Similar to conventional model comparison statistics, including the AIC (Akaike information criterion) and the BIC (Bayesian information criterion) for frequentist methods, the DIC seeks a balance between the overall fit of the model to the data and the complexity of the model for Bayesian models. The DIC values are automatically calculated by WinBUGS software as a byproduct during the inference procedures, and a lower DIC indicates a favorable model. The DIC values of the five candidate models were calculated to be 761,747, 761,885, 761,853, 761,912, and 761,814, respectively, confirming that Model I in the main analysis is the best model. Hypotheses H1 and H2 are further supported by the model comparisons of Model I and Model II (for H1), Model I and Model III (for H2), and Model I and Model IV (for H1 and H2). The placebo test, Model I vs. Model V, suggests that although the communication and functional behaviors of customers are not significant predictors, they are important controls in the SEM analysis.

Following the main analysis, we also conducted a series of robustness checks on the results. For the first robustness check, we explored the potential issues of outliers or influential observations. As noted from the summary statistics in Table 2, there are customers using hundreds of apps in one day. To assess the robustness of the estimations to the outliers or influential observations, we excluded those observations associated with customers in the top 1% (170 observations) of the distribution in terms of the overall frequency of app use. *Re*-estimating Model I on the subsamples produced no notable differences in the parameter estimations (see Table 3, panel 1).

For the second robustness check, we considered two shopping apps and measured customers' shopping behavior using only one shopping app at a time. As noted in the results of the factor analysis model in the main analysis (Fig. 1, factor loading $\lambda_{12} = 0.87$), the usage of the 'Taobao' app and 'Alipay' app is highly correlated, and thus, the effects of the influential factors on the usage of each shopping app should be similar to the results of the main analysis. We therefore conducted two evaluations for this robustness check, one with the usage of the "Taobao" app as the DV (dependent variable) and the other with the usage of the "Alipay" app as the DV. The results (see Table 3, panel 2) show that social capital (ξ_1) and hedonic habits (ξ_2) exhibit significant positive effects on the usage of each shopping app, and the effects are similar to those obtained in the main analysis.

Table 3
Estimation results for robustness checks.

Check 1 (outliers)		Check 2 (two shopping apps)		Check 3 (app categorization)	
b_1	−0.04 (0.007)	'Taobao' app as DV		b_1	−0.03 (0.005)
b_2	−0.02 (0.006)	b_1	−0.02 (0.007)	b_2	−0.02 (0.006)
b_3	0.06 (0.007)	b_2	−0.03 (0.007)	b_3	0.01 (0.008)
b_4	−0.05 (0.009)	b_3	0.03 (0.007)	b_4	−0.05 (0.008)
b_5	0.07 (0.007)	b_4	−0.02 (0.008)	b_5	0.06 (0.007)
γ_1	0.70 (0.044)	b_5	0.04 (0.008)	γ_1	0.56 (0.029)
γ_2	0.31 (0.058)	γ_1	0.18 (0.027)	γ_2	0.36 (0.052)
γ_3	−0.04 (0.062)	γ_2	0.25 (0.061)	γ_3	−0.06 (0.050)
γ_4	0.06 (0.076)	γ_3	−0.14 (0.075)	γ_4	0.07 (0.064)
		γ_4	0.48 (0.096)		
		`Alipay' app as DV			
		b_1	−0.04 (0.007)		
		b_2	−0.02 (0.006)		
		b_3	0.008 (0.008)		
		b_4	−0.07 (0.009)		
		b_5	0.07 (0.008)		
		γ_1	0.77 (0.032)		
		γ_2	0.34 (0.056)		
		γ_3	0.01 (0.078)		
		γ_4	−0.23 (0.102)		
Check 4 (communication)		Check 5 (shopping behavior on Nov. 9)			
b_1	−0.02 (0.005)	b_1	−0.03 (0.007)		
b_2	−0.02 (0.006)	b_2	−0.02 (0.006)		
b_5	0.06 (0.005)	b_3	0.00 (0.006)		
γ_1	0.65 (0.062)	b_4	−0.05 (0.007)		
γ_2	0.31 (0.042)	b_5	0.05 (0.007)		
γ_3	0.06 (0.054)	γ_1	0.52 (0.043)		
γ_4	0.09 (0.055)	γ_2	0.24 (0.055)		
		γ_3	−0.03 (0.061)		
		γ_4	0.08 (0.091)		

Note: only parameters in the structural equation are presented because the other parameters are estimated to be very similar to those of the main results; the values in parentheses are the associated standard errors; the symbols for each robustness check follow from Eq. (2) of Model I).

For the third robustness check, we evaluated the subcategorization of apps proposed by the mobile service provider. To assess the robustness of the estimations to the inclusion of applications in each subcategorization, we randomly excluded some apps in each subcategorization (e.g., 'QQ_Mobile_music' and 'Everyday_Sounds' were excluded from the categorization 'Music apps'). Re-estimating Model I using the new dataset (see Table 3, panel 3) produced similar results to those of the main analysis, which shows that our results are robust to the inclusion of apps in subcategories.

For the fourth robustness check, we further included an ego's calls and texts as proxies for the latent variable "communication behavior". In the main analysis, the latent variable "communication behavior" was constructed through the proxies only derived from the usage of communication apps on customers' mobile phones. However, customers' conventional wireless communication behavior, such as calls and texts, which were previously regarded as control variables in the main analysis, are potentially correlated with customers' mobile app communication behavior and can serve as extra proxies in the construction of the latent variable "communication behavior". The estimation results (see Table 3, panel 4) of this robustness check are similar to those of the main analysis, further strengthening the validity of the results of the main analysis.

In the main analysis, customers' shopping behaviors are measured on the day of the Double 11 event. As companies are encouraged to implement their marketing strategies on that day, there is a possibility that our estimation results are subject to the effect of promotional events. To alleviate the effects of promotional events, we conducted a fifth robustness check, which measures customers' shopping behaviors on a normal day using the data of customers' shopping app usage on Nov. 9. The corresponding customers' daily behaviors, such as hedonic habits, communication behavior, and functional behavior, are measured through the daily average values that are observed for the five days (Nov. 3–8) before Nov. 9 in our dataset. The results of the robustness check are given in Table 3, which show that the effects of social capital and hedonic behavior are still consistent with those of the main analysis, substantially alleviating the abovementioned concern.

3.5. From B2C to B2B: the possibility of strategic alliancew

In the main analysis, we utilized customers' usage of two different shopping apps, the "Taobao" app and the "Alipay" app, to measure customers' shopping behaviors. Behind these two apps are two distinct business players, which in our sample are actually two independent subsidiaries of a parent corporation, Alibaba Group. From the perspective of B2B marketing, their similar business nature enables us to explore potential cross-company synergy if the two form a horizontal alliance. Such a strategical alliance is rooted in a partial or complete sharing of valuable customer information across the two companies. As both companies can access the information of common customers in their shared customer database, they can strategically target these customers who are indeed heavy users of mobile shopping apps. Usually, heavy users can be more price-sensitive and have more sharply defined preferences (Kim & Rossi, 1994). Abundant social capital can effectively relax one's financial constraints (Calero, Bedi, & Sparrow, 2009), for instance, it allows a customer to frequently purchase online. We speculate that the effect of social capital (on sales) can be even more pronounced for these heavy users than for light users or nonusers. To test this speculation and explore the overall counterfactual consequences of the proposed strategic alliance, we conducted a subsample analysis with data from customers who used both shopping apps. The subsample contains 2626 mobile phone users who used both shopping apps at least once time on the Double 11 event. We summarized in Fig. 2 the results of this exploratory analysis, the other settings of which are being the same as those of the main analysis. The results again confirm that customers' social capital and hedonic habits are significant predictors of their shopping behaviors. While the effect size of hedonic habits remains similar, the effect size of social capital substantially increases,[5] suggesting that the two shopping apps can potentially boost sales by jointly targeting their common customers and focusing on those with high social capital.[6]

[5] We compare the effect sizes of this additional model with those of the main model due to the exploratory nature of this analysis. Since these two models are not nested with each other, the effect size should be interpreted with statistical caution. We encourage future research to more explicitly examine the effect size of extra gains from strategic alliance, which is not the scope of the current research.

[6] As the strategic alliance is composed by two apps (companies) which have an affiliation with the same parent corporation, the applicability of this test result can be undermined in other contexts, particularly when two firms are competitors or sell products with heterogeneous quality.

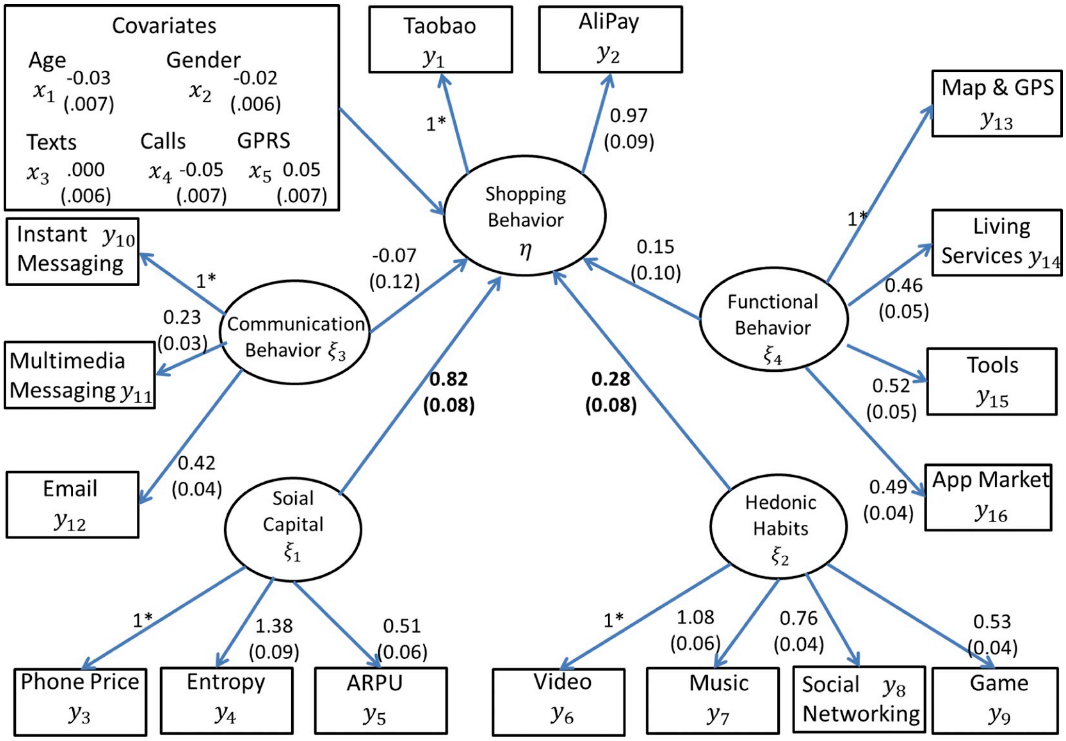

Fig. 2. The path diagram of SEM in the section exploring the possibility of a strategic alliance. The estimates of the factor loadings in the measurement equation and coefficients in the structural equation, together with their standard errors (in parentheses), are given next to the paths.

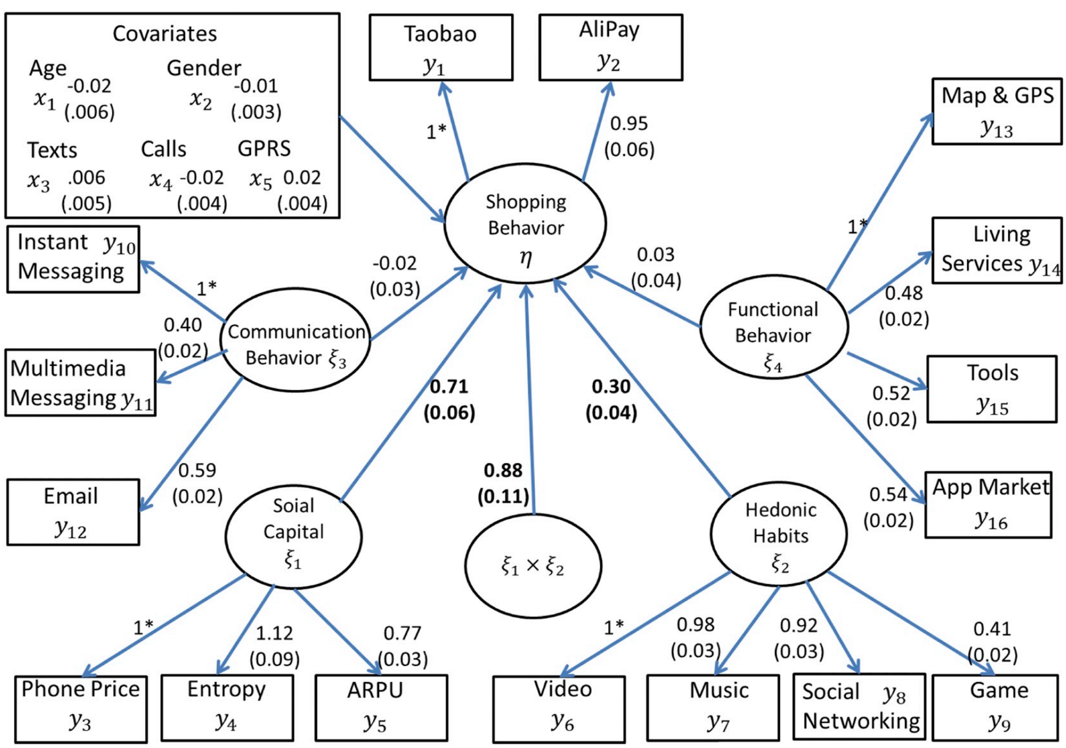

Fig. 3. The path diagram of SEM in the section exploring synergistic effect of social capital and hedonic habits. The estimates of the factor loadings in the measurement equation and coefficients in the structural equation, together with their standard errors (in parentheses), are given next to the paths.

3.6. *Exploring the synergistic effect of social capital and hedonic habits*

As discussed in the hypothesis development section, customers' social capital and hedonic habits are likely to exhibit a synergistic effect on their shopping behavior. That is, those with high social capital and high hedonic interests may shop online using their mobile phones more. To explore the possible synergistic effect of social capital and hedonic habits under our model setting, we considered including an interaction term of the latent variables, social capital (ξ_1) and hedonic habits (ξ_2), in the structural equation, and the new structural equation is given as follows:

$$\eta_i = \sum_{j=1}^{5} b_j x_{ij} + \sum_{j=1}^{4} \gamma_j \xi_{ij} + \gamma_5 \xi_{i1} * \xi_{i2} + \delta_i. \tag{7}$$

Structural Eq. (7), together with measurement Eq. (1), serves as the SEM approach for evaluating the synergistic effect; such an analysis also provides further evidence for the robustness of the results of the main analysis. The statistical inference procedures for SEM with interaction are similar to those of the main analysis. The PP *p*-value for this analysis was calculated to be 0.479, indicating a plausible model fit to the data. The estimation results and the corresponding standard errors are depicted in Fig. 3. We first noted that the factor loadings in the measurement equation and the coefficients for controls in the structural equation were estimated to be similar to those of the main analysis. Moreover, the respective positive effects of customers' social capital and hedonic habits were also revealed and similar to those of the main analysis. These findings further confirm the robustness of the main analysis. More importantly, the interaction term of the latent variables, social capital (ξ_1) and hedonic habits (ξ_2), exhibits a substantial positive effect ($\gamma_5 = 0.88$) on customers' shopping behavior, suggesting the potential synergistic effect of social capital and hedonic habits on customers' shopping behavior. That is, H3 is supported.

4. Discussion

The implications of our paper are fivefold and applicable to both academics and practitioners. First, this analysis contributes to the existing literature on mobile targeting (Luo et al., 2013). Mobile commerce has grown exponentially through the facilitation of mobile technology's distinct capacity for targeting. Mobile devices (e.g., mobile phones) are not mere substitutions for traditional online channels (e.g., computers). Rather, they complement traditional channels with more functions, such as time- and location-based services (e.g., GPS coupons), instant social interaction, and the instant identification of organizational issues, to serve customers and business partners. These features of mobile commerce allow an organization to better monitor its operations and performance than it previously had. Existing strategies on mobile targeting for marketers are based mainly on time- and location-based services (Chung et al., 2009; Ghose, Goldfarb, & Han, 2012; Luo et al., 2013). However, consumers' mobile telecommunication behaviors are becoming increasingly popular and drawing great attention from scholars, particularly in renowned journals (e.g., Eagle et al., 2009; Jia et al., 2017; Q. Wang, Li, & Singh, 2018). To date, we still know very little about those behaviors and their roles in mobile targeting because the big data related to those behaviors are still largely unexplored as a result of difficulties in accessing, storing, and analyzing such large datasets (e.g., there were 90-plus popular apps with over 20 million entry records from a major mobile service provider in China for this single analysis). This study is among the first to apply mobile app data to precisely capture various kinds of customer behaviors and the relationships therein, which helps to facilitate organizational targeting performance in terms of targeting both the right customers and the right business alliance partners.

Second, our findings add insight into consumers' hedonic values. Hedonic value is important because it has been found to be effective in determining customer involvement (Laurent & Kapferer, 1985), affecting consumers' product choices (Dhar & Wertenbroch, 2000), and eventually influencing firms' product designs and development (Voss, Spangenberg, & Grohmann, 2003). The hedonic dimensions of products or customer attitudes are conventionally measured through a survey or questionnaire (Voss et al., 2003), which is not directly applicable in the mobile targeting domain. This study adds to the theoretical developments of hedonic values in two respects. On the one hand, the hedonic habits of consumers can be evaluated based on their mobile telecommunication behaviors. As a result of the portability, proximity to owners, and multifunctionality of mobile devices, multidimensional data on consumers' hedonic activities using apps on their mobile phones are captured and can effectively describe their hedonic habits. On the other hand, customers' hedonic habits exhibit a substantial correlation with the shopping behaviors of customers. These findings provide valuable references for marketers to consider in mobile targeting; they could actively cooperate with mobile service providers to obtain customers' behavioral data and seek timely updates on customers' hedonic habits. Consultation firms could also pay more attention to customers' mobile data to derive insights for marketers. Based on customers' hedonic habits, marketers could directly target the right customers by themselves or seek appropriate alliance partners who already have such customers.

Third, this study complements the literature with a better understanding of the measurement of social capital. Social capital is an intangible force that helps to bind individual customers and organizations together by transforming the individuals into members of a community with shared interests and social relationships (Etzioni, 1996). The intangible nature of social capital limits its empirical measurement in real life. Consequently, a survey or questionnaire becomes the main way for firms to measure social capital (e.g., Mathwick, Wiertz, & De Ruyter, 2007). Realistic and timely empirical data, particularly mobile app and wireless behavior data, are rarely considered to summarize customers' social capital. Our proposed measurement of social capital based on individuals' telecommunication connections and behavior data, which particularly absorbs social network information, provides an alternative and relatively unbiased measurement of social capital. As big data accumulate in firms and big data analytics become firms' rituals, our proposed measurement of social capital has the advantage of immediacy (e.g., surveys are carried out in certain periods and usually lag behind sudden market changes, but calculations based on big data can be conducted every minute), lower cost (without the need to pay for survey participants), and higher accuracy (with the improvement of big data analytics and algorithms).

Fourth, this analysis reveals possible synergy between customers' social capital and hedonic habits. Such an effect in itself complements the theory of the effects of customers' social capital and hedonic values (on firm sales) by simultaneously considering and formulating them. This result provides important insights for marketers to consider in mobile targeting. When trying to target the right customers or alliance partners, it is not sufficient for marketers to consider the isolated customer types of high social capital or deep hedonic interests. Marketers could improve targeting by simultaneously considering the features of social capital and consumers' hedonic values.

Finally, this study harnesses the power of mobile-phone big data to solve a practical marketing problem of targeting the type of customers who most substantially reacts to promotional events, which further confirms that big data are valuable assets for firms and organizations. Through the use of a large dataset of customers' mobile apps, wireless behavior, and demographic data, this analysis precisely captures various kinds of customer activities and interests and reveals that significant relationships exist between customers' shopping behavior and their social capital and hedonic habits. The results complement the literature on behavioral big data. Our findings, though generated in a B2C context, can also be generalized to a B2B context, because those mobile-phone big data allow organizations to better understand not only their customers but also their business partners, competitors, and players in B2B markets in general. Great efforts in decoding big data related to customers have been made for B2C markets, which help B2C market players improve their marketing strategies and eventually their sales performance (e.g., Khalilzadeh & Tasci, 2017; Liu, Teichert, Rossi, Li, & Hu, 2017). Our work suggests that firms in B2B markets should also leverage the potential of big data analytics and can benefit substantially from strategical alliances with their business partners. By

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sharing the information regarding their common customers, firms may jointly understand and target those most profitable customers whom they cannot identify on their own. As we show in our analysis, if e-commerce firms (i.e., “Taobao” and “Alipay”) can form a horizontal alliance[7] and together target customers that use both shopping apps (i.e., heavy users of mobile shopping apps), the positive effect of social capital is even more pronounced for these common (heavy) users than for light users or nonusers. In addition, our manuscript suggests that by combining frozen data sources from various departments across firms and employing appropriate empirical methodologies (e.g., Bayesian SEM in this study), firms can exploit the accumulated big data to help them in various organizational operations and marketing strategies. As exemplified by our work, we leverage wireless telecommunication data to measure customers' social capital and utilize mobile application data to reflect their physiological interests. These previously isolated data sources are able to be merged and, together, help companies develop effective and efficient targeting strategies, which eventually lead to the improved sales performance of the firms and the creation of sustainable competitive advantages.

The present study has several limitations that could suggest promising directions for future research. First, we use app usage on Taobao and Alipay as a proxy for shopping behavior. Even though Taobao and Alipay are the largest e-commerce players in China, some customers make purchases through other e-commerce platforms, or directly shop on brands' self-built platforms. Future research could consolidate individual customers' shopping information across multiple platforms and explore the differential effects of mobile targeting in the various communities (e.g., centralized e-commerce platforms vs. brands' self-owned platforms). Second, although we have explored the possibility of firms' strategic alliances by assuming that they are willing to share their customer databases and focus on common customers, our analysis has not explicitly identified the impact of strategical alliances, such as examining the effect of the extra benefits gained from adopting strategic alliance. Future research could use better research designs or statistical methods (e.g., difference in differences comparisons) to accurately identify the effects of strategic alliances in mobile targeting contexts. Another worthwhile avenue for future research relates to the general extension of mobile targeting strategies to B2B markets. Our mobile shopping data allow us to look at the possibility of a horizontal alliance, i.e., to focus on the common customers that were potentially the pool of customers that firms with homogenous products compete for. Considering the complicated nature of the B2B market, future research can also examine other forms of strategic alliances, such as vertical alliances, and explore the potential substitution or supplement effects between different categories of firms when they form alliances. For example, in the context of mobile targeting, the publication industry could be a vertical supplement to the education industry but possibly a horizontal substitution for the e-books industry.

5. Conclusion

Although the present study leaves numerous avenues for future research, our data analytics results reveal that mobile targeting can help firms identify consumers' hedonic value in the online shopping process as well as their social capital, which both lead to increased firm sales. This work provides interesting findings that connect big data, mobile targeting, and online consumer behavior, thus providing further insights into business practice in industries. We hope that our empirical study not only answers some questions but also stimulates future research.

[7] The strategic alliance in our context is composed of two apps (companies), which have an affiliation with the same parent company. As these two apps are highly independent in terms of operations and management, inferences made based on the results are at least partially applicable to the strategic alliance of potential competitors; future researchers are encouraged to more explicitly examine the scenario when strategic alliance is formed between two competing firms.

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