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Consumer perceived value preferences for mobile marketing in China: A mixed method approach

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ABSTRACT

This study aimed to identify a new framework for consumer perceived value (CPV) and evaluate the dynamics of relative importance of different dimensions of CPV in the context of mobile marketing. Laddering interviews were conducted to capture the essence of CPVs, and then text-mining techniques were applied to extract key consumer values from the interviews. Six dimensions of CPV, namely, design, emotional, functional, monetary, guarantee, and social, were identified. The construct validity of these six dimensions was demonstrated through a rigorous sorting process. A best–worst scaling (BWS) survey was then implemented based on these six value dimensions to investigate consumers' preference for each dimension in three critical decision-making phases of mobile marketing campaigns. Statistical analysis of the BWS data showed that significant dynamic differences exist among these six value dimensions in each phase. Gender difference and consumer heterogeneity were also presented. Theoretical and managerial implications were discussed.

1. Introduction

The implementation of the "Internet +" program and the continuous technological innovation in China have facilitated the rapid growth of the Chinese mobile payment market. According to Reportlinker (2017), the Chinese mobile transaction volume for 2017 was approximately RMB 294.97 trillion. This growth is indicative of an upsurge of 41.4% from RMB 208.6 trillion in 2016 and is expected to continue over the following years to hit RMB 793 trillion in 2021. The volume of third-party Chinese mobile payment transactions reported in 2015 was RMB 21.96 trillion, with 90% of the market seized by Alipay and Tenpay (Reportlinker, 2017). Both mobile payment methods are integrated with the WeChat official account marketing. The tremendous growth of the Chinese mobile payment and advertising market has stimulated a stream of research on aspects of consumer behavior in a mobile-dominated marketing world (Wolfgang et al., 2017).

Consumer perceived value (CPV) is an important concept in the marketing field. CPV can exert a significant influence on consumer's attitude (e.g., Aydin and Karamehmet, 2017; Izquierdo-Yusta et al., 2015), satisfaction (e.g., Li et al., 2015; Zboja et al., 2016), loyalty (e.g., Koller et al., 2011; Kuikka and Laukkanen, 2012), and purchase intention (Hsiao and Chen, 2016; Wang et al., 2018). As consumers become increasingly demanding and value-conscious (Leroi-Werelds et al., 2014), capturing the essence of CPV has become important for companies. In addition, the mobile phone has become an integral part of our daily lives, and companies are increasingly turning to apps to gain additional consumers (Stocchi et al., 2017). Therefore, we have witnessed a huge increase in expenditure on mobile advertising (Bart et al., 2014). As consumers spend more time on their mobile devices, mobile marketing is clearly no longer a matter of choice for companies but one of their survival strategies (Earl and Feeny, 2000).

CPV, however, is a comparative, personal, and situational (specific to the context) concept (Miao et al., 2014). The definition of value in marketing literature has evolved over time (Chi and Kilduff, 2011). The application of CPV to specific products or services is a critical issue for companies (Ravald and Grönroos, 1996). Compared to traditional marketing, mobile marketing has unique features, such as interactivity (Ström et al., 2014; Wang et al., 2015; Wu and Hsiao, 2017), convenience (Andrews et al., 2016; Shankar et al., 2016; Ström et al., 2014), personalization (Shankar et al., 2016; Tang et al., 2013), and effectiveness (Andrews et al., 2015; Hofacker et al., 2016). These features facilitate the essence of CPV to evolve. Hence, for companies to understand consumer value perception and survive in this new marketing context, exploring the new characteristics of CPV in the mobile marketing context is necessary.

To analyze different consumption situations and product types,

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researchers have proposed several multi-dimensional models of CPV (e.g., Chaudhuri and Holbrook, 2002; Hsu and Lin, 2016; Sheth et al., 1991; Sweeney and Soutar, 2001). Chaudhuri and Holbrook (2002, p. 33) proposed a two-dimensional model (utilitarian value and hedonic value) by using brands as the units of analysis. Sheth et al. (1991) presented a theory to explain why consumers make their choices and identified five consumption values that influence consumer choices. On the basis of Sheth et al.'s (1991) framework, Sweeney and Soutar (2001) developed a PERVAL scale to measure four value dimensions of buying durable goods. The aforementioned multi-dimensional models of CPV were discussed in the context of traditional in-store consumption situations. Most researchers applied these typical models to extend the research landscape from in-store consumptions to service and online business during this decade (e.g., Chiu et al., 2014; El-adly, 2018; Williams and Soutar, 2009). Furthermore, most studies conducted on mobile services still adopted existing multi-dimensional models (e.g., Karjaluoto et al., 2018; Yang et al., 2018).

Prior research has distinct empirical contexts and focused on different consumption environments. Traditional businesses are usually constrained by location and time-consuming processes. Companies would be inconvenienced to communicate with their customers if customers leave the store or do not have access to a computer. Mobile marketing is a set of practices that enable organizations to communicate and engage with their audience in an interactive and relevant manner through any mobile device or network and can serve as a tool for involving customers in co-creation activities independent of time and place (Ström et al., 2014). Mobile marketing has several characteristics. For example, first, mobile payment is generally embedded in a mobile marketing campaign that allows consumers to purchase products and services anytime and anywhere. The convenience and effectiveness of mobile marketing make consumers perceive functional value differently (Ström et al., 2014). Second, mobile social media commonly used in a mobile marketing campaign can make consumers interact with companies to obtain information or customer services they need at any time and any place. The interactivity of mobile marketing improves consumers to perceive social value in a different manner (Ström et al., 2014; Wang et al., 2015; Wu and Hsiao, 2017). Third, precision marketing is widely applied in mobile marketing. Companies can collect more detailed information (e.g., location) from user behavior data with mobile Internet and mobile phone, as well as target their consumers more accurately and develop personalized marketing campaigns accordingly. The personalization of mobile marketing facilitates consumers to perceive emotional value positively (Shankar et al., 2016; Tang et al., 2013). Moreover, mobile marketing has improved dramatically with the development of smart phone usage and mobile technologies (Ström et al., 2014). As business models become increasingly complex, consumers perceive value in different ways (Chi and Kilduff, 2011). In addition, based on our review, no research has investigated the dimensions of CPV in the context of mobile marketing. If case any new dimension differing from those typical dimension models exists, it remains unknown. Hence, identifying the dimensions of CPV in a new business context is necessary. These aforementioned arguments lead to our first research question.

RQ1. What are the dimensions of CPV in the context of mobile marketing (MCPV)?

The role of consumers as co-creators of value should be explored (See-To and Ho, 2014) because of the communication and engagement between organizations and consumers through the mobile marketing process (Wu and Hsiao, 2017). CPV is personal and specific to the context (Miao et al., 2014). Thus, the mobile environment changes the consumer value perception in a new manner. Moreover, consumers participate in a mobile marketing campaign, which typically comprises several decision-making phases (Pescher et al., 2014). Sheth et al. (1991) indicated that different values influence consumer decisions. Therefore, values perceived by consumers in each phase would have different effects on their decision-making processes. Analyzing the changes in CPV at various phases and how consumers evaluate different dimensions of value in each phase is thus necessary. For example, Wu (2017) identified 4 primary dimensions and 13 sub-dimensions of experiential quality value in a coffee chain. They found that affective quality is the most primary dimension of experiential quality perceived by coffee chain customers. However, research on consumer preference for a specific CPV dimension merely gained interest recently. Only a few studies have focused on consumer preference for each specific value dimension. Moreover, though CPV was argued to dynamically change, no further empirical studies have demonstrated this statement. Hence, these research gaps lead us to investigate the following questions.

RQ2. Do consumers differ in their assessment of the importance of value dimensions in each decision-making phase of a mobile marketing campaign?

RQ3. Does the importance of value dimensions dynamically change across a mobile marketing campaign?

This study aims to identify a new dimensional framework of CPV in the mobile marketing context and evaluate the dynamic, phase-dependent importance of dimensions of CPV. This study contributes to the CPV literature in the following perspectives. First, this research proposes a new dimension framework of MCPV. Second, it provides a "dynamic view" to assess the importance of value dimensions as consumers go through a mobile marketing campaign. Third, it identifies significant differences in consumer preference for various value dimensions. Fourth, consumer heterogeneity and gender difference in terms of preference for value dimensions are investigated. Therefore, this study facilitates a thorough understanding of CPV and fills the research gaps with regard to CPV in the mobile marketing literature.

Section 2 provides a brief background of the general research framework. Then, the mixed method and data analysis employed were presented in Section 3. Finally, the Sections 4 and 5 discusses the results and implications.

2. Theoretical background

2.1. Consumer perceived value

Consumer perceived value (CPV) provides a basis for understanding consumer behavior in the context of various e-services (Li and Mao, 2015). CPV has been demonstrated as an important indicator for predicting consumer satisfaction, loyalty, and purchase intention (e.g., Chiu et al., 2014; El-adly, 2018; Faruk, 2018). It is regarded as an essential basis for a company's success because of its significant effect on loyalty (García-Fernández et al., 2018). CPV involves the overall assessment on the discrepancy between the perceived benefit and cost of obtaining the products or services (Zeithaml, 1988). Woodruff (1997) linked products with product usage and connected consequences experienced by goal-oriented customers. Hence, CPV is defined as the perceived preference of consumers for and evaluation of the product attributes, attribute performances, and consequences arising from usage that enables (or hinders) the attainment of consumer goals and purposes in various situations. This definition is based on a means–end type of model, which emphasizes that value comes from the learned perceptions, evaluations, and preferences of consumers. This study aims to analyze how consumers perceive and assess value in a mobile marketing campaign. Woodruff's (1997) approach was considered as the best choice for consumer high-involvement situations (Leroi-Werelds et al., 2014). Therefore, Woodruff's (1997) definition was adapted in this study and means–end chain theory was employed to develop the interview questions. In the current study, MCPV refers to a customer's assessment on and preference for mobile marketing campaign attributes, attribute performance, and consequences of participating in the campaign that enables (or hinders) the attainment of consumer goals and purposes.

Several multidimensional models of CPV have been proposed in research. Motivation and goal orientation are the two main perspectives to classify the dimensions of CPV (Zhang et al., 2017). For motivation orientation, CPV is generally classified into a two-dimensional model (utilitarian and hedonic values) (e.g., Chiu et al., 2014; Holbrook and Hirschman, 1982; Park and Park, 2009). From this perspective, products are assessed solely from the basis of utilitarianism, depending on how well the product can achieve its intended purpose and perform its function. Judgment through hedonic criteria is based on the consumers' appreciation for the product. For goal orientation, consumers purchase the product or services to satisfy their goals. From this perspective, customers seek for social, emotional, altruistic, and hedonic values (Holbrook, 2006). Sheth et al. (1991, 1992) proposed a five-dimensional model which considered social, functional, emotional, conditional, and epistemic values. This model laid a solid foundation for expanding the structure of CPV. On the basis of this five-dimensional model, Sweeney and Soutar (2001) then proposed a four-dimensional CPV model which included social, emotional, functional (price), and functional (quality and performance) values. Subsequently, multi-dimensional models were presented from this view (e.g., Chi and Kilduff, 2011; Williams and Soutar, 2009). However, these typical multi-dimensional models were developed in the early 1990s and 2000s and did not consider the characteristics of mobile marketing. Nevertheless, studies that have explored CPV in the mobile setting (e.g., Andrews et al., 2012; Karjaluoto et al., 2018; Yang et al., 2018) still adopted the existing models. The different dimensions of CPV in the context of mobile marketing are still unclear. In this case, the current study aims to develop a multidimensional model for CPV in the context of mobile marketing (MCPV).

2.2. Means-end chain and uses and gratification theory

Means–end chain (MEC) theory assumes that consumer behavior is directed by goals in general and can be used to explore consumers' behavior through a goal hierarchy (Gutman, 1997). MEC suggests that products in relation to consumers can be represented by three levels: attributes (qualities, characteristics, and physical features of a product), consequences (subjective experiences derived from product use), and desired end-states (consumer's core value, purposes, and goals in life) (Woodruff, 1997). Woodruff and Gardial (1996) indicated that MEC theory can be adapted to capture the essence of consumer value. They proposed a consumer value hierarchy and suggested that consumers perceive value in a Means–end mechanism. This theory was then widely used in various situations. For example, Lin and Fu (2018) adopted MEC theory to propose a framework to evaluate online advertising effect. Xiao et al. (2017) used MEC approach to investigate consumer goal structure in online group buying contexts. Jung et al. (2017) employed this goal hierarchy approach to analyze the relationship between the use of Facebook and psychological well-being in young adults.

Uses and gratification theory (UGT) is an audience-centered approach that explains why and how users employ media to satisfy their needs, which lead to differential patterns of media use or behavior (Rubin, 2009). It also assumes that media selection and use are goal-oriented and motivated by users' desire to gratify their needs (Kim et al., 2016). In other words, UGT can be used to explore how users deliberately seek out media to satisfy certain needs or goals, such as relaxation, entertainment, or socialization. Hence, consumers have different motives when using media.

UGT provides a psychological perspective to understand users' active use and choice of media content or platforms. On the basis of UGT, Okazaki (2004) indicated that perceived infotainment (i.e., a combination of information and entertainment) is one of the main motives in advertising acceptance. Nysveen et al. (2005) also found that perceived usefulness, expressiveness, control, enjoyment, and social influences have a strong impact on a user's intention to use mobile services. Notably, consumers perceive values based on their goals using mobile services (Hanzaee and Ghafelehbashi, 2012; Kim and Hwang, 2012). Pai and Arnott (2014) adopted MEC and UGT theories together to examine social network sites adoption. Gan and Li (2017), from a perspective on UGT, explored the effect of gratifications on the continuance intention to use WeChat in China. In those studies, MEC theory generally presents a hierarchical point of view that can be used to identify consumers' goals. Hence, these two theories can lay the foundation for our study.

2.3. WeChat official account

WeChat official account (WOA) is an interactive marketing platform in China. Developers, merchants, celebrities, and organizations can communicate and interact with consumers through text, images, voice, and videos via their WOAs. Consumers can subscribe to official accounts to obtain various Internet services. The influence of product recommendations on impulse buying has been examined on WeChat social commerce (Chen et al., 2018a, 2018b). Liang and Yang (2017) empirically investigated the impact of WeChat user motives and trust on user behavior and word-of-mouth intentions on a WOA-hosted travel agency. WOA is currently one of the most widely used marketing media in China (Liang and Yang, 2017).

Balasubramanian et al. (2005) presented a three-stage process of a typical purchase situation, namely, forming a consideration set, choosing a product, and buying the product. These steps are the well-known stages that comprise the consumer decision-making process (Shankar and Balasubramanian, 2009). In a WOA campaign, consumers receive a set of marketing messages and decide whether to read or click on the short titles in the first phase (Fig. 1a to 1b; Fig. 1a displays the message at the top as the selection). In the second phase, consumers can click on the short title to read the detailed campaign article and decide which product to buy (Fig. 1b to 1c; Fig. 1c illustrates this option on the "Armani watch"). In the last phase, consumers decide to purchase the product through the campaign (Fig. 1c to 1d). These phases match typical stages of a purchase situation. Fig. 1 illustrates these phases for a product in Amazon.cn. Notably, if consumers are uninterested in these messages, then they may immediately abandon any phase. However, if consumers are uninterested but deem these messages useful for others, then they may forward it (Fig. 1e). Meanwhile, consumers who are uninterested in this campaign but think this account will be useful in the future may subscribe to it (Fig. 1b).

WOA marketing has emerged as the most commonly used mobile marketing channel in China. However, research on this area is limited. Thus, WOA marketing is chosen as the research object in this study.

3. Methodology

3.1. Creation of MCPV dimensions

The investigation and development of MCPV dimensions were conducted in three stages. The first stage was exploring the essence of MCPV through face-to-face interviews. The next stage was text-mining analysis and focus group discussion of interview text data to create pools of keywords. In the third stage, panels of judges sorted the initial keywords into separate categories based on their similarities and differences. The keywords could also be examined or eliminated by the judges for inappropriate expression or ambiguous word usage.

3.1.1. First stage: interview

At this stage, interviews were conducted to explore ideas and opinions about MCPV. Interviewers were trained in several classes to understand the concepts of CPV and mobile marketing and the objectives of this interview.

The laddering interview technique was used in this study to explore

a. Receive marketing messages

b. Click on a title to open a detailed article

c. Click on a link in the article to obtain information about the product

d. Purchase the product

e. Forward the article or product to friends

Fig. 1. Marketing phases of WeChat official accounts.

the essence of MCPV. Laddering is a commonly used interview method for triggering MEC (Reynolds and Gutman, 1988) and is widely accepted to explore personal preferences for objectives or activities in IS research (e.g., Xiao et al., 2017; Jung et al., 2017). This technique allows researchers to probe deeper into the responses to derive customers' higher-level goals (Xiao et al., 2017). In laddering, respondents need to answer a series of "Why?" questions to explore their reasons for wanting a particular attribute, leading to the promotion of the next level of abstraction (Gutman, 1997). This series of continuous questions creates a series of elements. Each element is directly linked to its adjacent elements, which can capture the essence of CPV (Woodruff, 1997). Thus, laddering can examine the extent to which consumers perceive the value for achieving their hierarchy goals through participation in a mobile marketing campaign.

Interview questions in line with laddering and MEC theories were developed (Table 2). The questions were generally asked in the following order: (1) Have you ever done the activity? (2) What factors drive you to do that activity? (3) Why do you do it? (4) Why is the factor important? This type of means–end chain questionnaire can provide knowledge on the hierarchical goal structure (i.e., activities → mediated goals → ultimate goals) (Jung et al., 2017). As shown in Table 2, we asked interviewees about five activities (clicking, reading, purchasing, forwarding, and subscribing) and they answered the follow-up questions for each activity. To acquire deeper reflections from interviewees, more opening questions close to our laddering questions were asked during the interview. Interviewees were encouraged to provide answers to all questions.

The sample population of this research is WeChat users in China. A total of 400 WeChat users were randomly invited to participate in our research. At first, each interviewee was asked a series of questions about their experiences in joining mobile marketing campaigns, particularly in WeChat. We selected users who have joined in at least one WeChat official account marketing campaign for further interviews. Finally, the interviews involved 179 experienced respondents from various areas in China and with different occupations. Experienced interviewees were shown a typical mobile marketing campaign through

Table 1
Demographic features of interviewees.

	Categories	Frequency	Proportion
Gender	Female	79	44.1%
	Male	100	55.9%
Age	Under 18	5	2.79%
	18–25	153	85.47%
	26–35	18	10.06%
	Above 35	3	1.68%
Occupation	Employees	16	8.94%
	Students	151	84.36%
	Others	12	6.70%
Education	High school and below	15	8.38%
	Bachelor	158	88.27%
	Others	6	3.35%
Experience	Within 1 year	11	6.15%
	1–2 years	26	14.53%
	2–3 years	60	33.52%
	3–4 years	44	24.58%
	4–5 years	18	10.06%
	5 years or more	20	11.17%
Open WeChat	Not every day	23	12.85%
	Less than 5 times	31	17.32%
	5–10 times	32	17.88%
	10–20 times	35	19.55%
	20–30 times	35	19.55%
	Over 30 times	23	12.86%
Behavior **(multiple choice)**	Forward	84	46.93%
	Subscribe	154	86.03%
	Click short title	85	47.49%
	Click link in article	53	29.61%
	Purchase	74	41.34%

a WeChat official account to clarify different phases (Amazon was used as an illustration). Following this notion, interviewees were asked to recall an impressive WeChat marketing campaign in which they had recently participated. Interviewees were then asked what factors were important for them in each phase and why. Each interview took approximately 30–40 min. The interview was conducted from March 2016 to January 2017. Table 1 provides the demographic feature of the respondents.

3.1.2. Second stage: text-mining analysis

We obtained 179 consumer responses from our interviews. Each respondent was interviewed for 30–40 min, and each interview was recorded on audio and subsequently transcribed. We initially read each interview data and took down notes of our early impressions in order to become familiar with the interview data. After eliminating demographic data and attribute information (which were collected by using the filtering question Q3 listed in Table 2), we obtained text data with 95,904 Chinese characters for further analysis.

The traditional analysis methods for interview data usually deal with small samples of no more than 50 people (Ritchie et al., 2003). In this study, we interviewed 179 WeChat users and obtained more than 90,000 texts in Chinese characters. Compared with the traditional time- and labor-intensive human content analysis of textual information, data and text mining can effectively reduce the amount of time and manual labor that is consumed in identifying insights and patterns from large collections of text (Wu, 2013). Schmidt (2009) added that text mining techniques can be used to obtain better insights into the text data collected from in-depth interviews, open-ended responses, and focus group transcripts. Several researches have also employed text mining to deal with interview data (e.g., Chen and Barbour, 2017; Hewett et al., 2009; Schmidt, 2009). Furthermore, the continuous improvements in computer hardware architecture and software algorithms have greatly increased the accuracy of text data analysis (Schmidt, 2009). Although the effectiveness of traditional qualitative analysis has been validated (Lee and Hubona, 2009), various types of software (e.g., Nvivo, Atlas, Leximancer, and R language) have been utilized to perform various

Table 2
Main interview questions.

Please answer the following questions based on ***an impressive experience*** when you recently participated in a WeChat official account marketing campaign.

1. What is your main purpose for subscribing to this WeChat official account? Why?
2. What factors did you take into account when you participated in this mobile marketing campaign? Why?
3. Have you forwarded, subscribed, clicked/read, and read the detailed information (to register or purchase)?
4. What factors influence you to forward these messages? Why?
5. What factors influence you to subscribe to this account? Why?
6. What factors influence you to click/read the title messages? Why?
7. What factors influence you to read/click the link(s) in the article? Why?
8. What factors influence you to participate in this campaign, such as registering or purchasing? Why?
9. Among these factors, which one do you deem the most important?
10. Why do you consider this/these factor(s) are the most important?
11. Which factors/events/activities had the most impression on you in the entire process of your participation?
12. What is your overall impression of this official account?

text-mining and analysis functions, such as word frequency counts and semantic coding, which complement the manual coding efforts of researchers. Moreover, as Delen and Crossland (2008) indicated, text mining is the process of potentially useful information from various unstructured data sources and it can be used to identify key phrases from unstructured data. Therefore, text mining is appropriate for handling textual data and for analyzing our interview data.

We used the TM program package of R language (Feinerer et al., 2008) for the text mining analysis. The analysis started with the words segment. First, numbers were deleted from the text, and we used the plug “Rwordseg” in R language, which specifically deals with Chinese characters, to segment sentences into single words. Secondly, we inputted the “stopwords” file into the program to eliminate all meaningless words. The original “stopwords” list contains 1000 usual words. We also added to this list several special words related to WeChat and brands, including “微信” (WeChat), “朋友圈” (moments), and “京东” (Jingdong). In this process, we carefully inspected the original text data and results in each round of eliminating “stopwords”. When meaningless words were found in the results, we added these words to the stopwords list and performed the process of elimination again until we obtain a clean wordlist. Third, we transferred the “clean” wordlist as a text corpus into vectors and then generated a document term matrix. Fourth, we identified those words with a term frequency of greater than five times in the result list.

Mostafa (2013) performed text mining on 3516 tweets and then used a word frequency algorithm to select those keywords with frequencies of greater than 10 times. To retain more information, after removing stopwords from the text dataset, we extracted those keywords with frequencies of greater than five times by using the term frequency algorithm. We obtained 263 words from this procedure. However, many of these words were either synonymous or almost had the same meaning, such as “实用” (practical) and “实用性” (practicability), “图片” (picture) and “配图” (picture), “视频” (video) and “小视频” (short video), and “游戏” (game) and “小游戏” (mini-game). Furthermore, several words were not related to the main objectives of this study, such as “东西” (item), “白条” (debit product from JD.com), and “外面” (outside), all of which were removed. A total of 87 keywords were eventually retained. Fifth, we tracked each word into the original text dataset to examine its context and to ensure that it has meaningful information. A total of 3 mobile marketing managers and 10 WeChat official account subscribers were invited to a discussion group to clarify these keywords. The group merged those words with a similar meaning (e.g., conflating “有意思”, “有趣”, and “好玩” to “interesting,” and conflating “便利”, “便捷”, and “方便” to “time efficient”) and applied general words to include more words together (e.g., applying “helpful” to contain the context meaning of “工作” (work), “学习” (learning), and

Table 3
Initial dimensions.

Dimensions	Factors derived from the interviews	Items derived from prior research
Emotional value	■ Match my hobby ■ Feel good ■ Like the account ■ Good impression ■ Touching ■ Empathy ■ Meaningful ■ Satisfied	Sweeney and Soutar (2001) (Emotional value) ■ Is one that I would enjoy ■ Would make me want to use it ■ Is one that I would feel relaxed about using ■ Would make me feel good ■ Would give me pleasure
Functional value	■ Helpful ■ Useful ■ Efficient ■ Knowledge ■ More choices ■ Flexible payments ■ Purchase directly	Chaudhuri and Holbrook (2002) (utilitarian value) ■ I use this product frequently ■ I rely on this product ■ This product is a necessity for me Chiu et al. (2014) (utilitarian value) ■ Product offerings ■ Product information ■ Convenience
Monetary value	■ Affordable price ■ Special offers ■ Free gifts ■ Cheap	Chi and Kilduff (2011) (price value) ■ Is reasonably priced ■ Offers value for money ■ Is a good product for the price ■ Would be economical
Social value	■ Agree with the comments ■ Comments make sense ■ Social identity ■ Word-of-mouth ■ Good dissemination ■ Interesting comments ■ Interesting marketing campaign ■ Interesting contents ■ Interesting games ■ Interesting videos	Sweeney and Soutar (2001) (Social value) ■ Would help me to feel accepted ■ Would improve the way I am perceived ■ Would make a good impression on other people ■ Would give its owner social approval Chiu et al. (2014) (Social value) ■ I go shopping on this website with my friends and family to socialize. ■ I enjoy socializing with others when I shop on this website. ■ Shopping on this website with others is a bonding experience.
Guarantee value	■ Good product design ■ Good quality ■ Good reputation ■ Guarantee policies ■ Transparent process ■ Reliable information	Chi and Kilduff, 2011 (quality value) ■ Has consistent quality ■ It is well made ■ Has an acceptable standard of quality ■ Would perform consistently
Design value	■ Attractive title ■ Neat layouts ■ Original content ■ Good display ■ Appropriate pictures ■ Exquisite pictures ■ Special ads ■ Elegant words	New dimension

"资料" (document)). A total of 43 words remained. We tracked these 43 words into the original text to add contextual information and to make them more understandable (see Table 3).

3.1.3. Third stage: sorting

Several multi-dimensional models of CPV have been proposed in prior studies (Appendix A). Compared with those models, 43 factors were preliminarily classified into six dimensions (Table 3).

Table 3 shows that the majority of the factors can be classified explicitly in line with prior studies. EV has a meaning that is similar to that in Sweeney and Soutar's (2001) research. It also refers to feelings or affective states of consumers. FV refers to the satisfaction of consumers' practical needs and improvement of their efficiency. This definition is similar to that of the utilitarian value proposed by Chaudhuri and Holbrook (2002). "Flexible payments" and "purchase directly" on mobile devices are new characteristics of mobile marketing that can improve the purchase efficiency and convenience of consumers. Hence, we preliminarily classified these factors into the FV dimension. MV is similar to that of Chi and Kilduff's (2011) price value, which derives from the reduction of costs. SV refers to social identity and interactivity when consumers join a mobile marketing campaign. Interviewees claimed that when they come across "interesting comments/marketing campaign/contents/games/videos" in a mobile marketing campaign, they feel the desire to share these messages with friends. Furthermore, these features induce an increase in the number of forwarding and sharing. Hence, we preliminarily classified these factors into the SV dimension. GV refers to expectation of reduction of risk, which extends the quality value dimension based on Chi and Kilduff's (2011) framework. When consumers participate in mobile commerce, consumers not only take the quality of goods into account, but also consider the reliability of the information (Wu and Hsiao, 2017), reputation of the company (brand image) (Chen et al., 2018a, 2018b), and after-sales services (Pee et al., 2018). Hence, we preliminarily classified these factors into GV. Importantly, we found consumers' concern for design aesthetics in mobile marketing campaigns. Hence, a new dimension was proposed, namely, DV, which includes factors that remain to be further explored. Table 4 summarizes the definitions of the six value dimensions.

To assess the construct validity of the six dimensions and identify any particular keyword that may still be ambiguous, we followed Moore and Benbasat (1991)'s sorting process.

a. **General.** Judges were invited to implement the sorting process in each sorting round. The judge group was composed of a professor, a

Table 4
Dimensions and definitions.

Dimension	Definition
Emotional value	Consumers' preference and assessment for the extent of various content and services in this mobile marketing campaign which satisfy their emotion requirement.
Functional value	Consumers' preference and assessment for the extent of products or services in this mobile marketing campaign which satisfy their practical needs or improve their task efficiency.
Monetary value	Consumers' preference and assessment for price and promotions in this mobile marketing campaign.
Guarantee value	Consumers' preference and assessment for the extent of reduction of risk in this mobile marketing campaign.
Social value	Consumers' preference and assessment for interactivity and social identity when they participate in this mobile marketing campaign.
Design value	Consumers' preference and assessment for design aesthetics and creativity of this mobile marketing campaign.

secretary, an administrative clerk, and a student. The judge group will be composed of different people at each round. To minimize the potential of interpretational confounding, the judges were not informed of the underlying dimensions and were asked to provide their own labels and definitions for categories. If the definitions match the dimensions' intent, then construct validity will increase (Moore and Benbasat, 1991). Moore and Benbasat (1991) also suggested that if an item is consistently classified into a particular category, then it is regarded as proof of convergent validity with the related constructs and discriminant validity with the others.

b. **Sorting procedures.** We printed each keyword on a 5 × 5 cm index card. The cards were randomly arranged before being given to the judges. Each judge classified the cards into categories and labeled each category of keywords independently from other judges. Before the judges sorted the cards, a standard set of instructions was read to the judges, who were then allowed to ask questions to ensure they understood the procedure comprehensively. A trial was then conducted by each judge on 12 sample items unrelated to the dimensions of this study. In this case, any misunderstanding on the instructions was clarified.

c. **Inter-rater reliabilities.** Two measurements were used to evaluate the reliability of the sorting process conducted by the judges. First, Cohen's kappa coefficient (Cohen, 1960) was used to measure the level of agreement in classifying the keywords for each pair of judges in each sorting round. Kappa scores greater than 0.65 are acceptable (Moore and Benbasat, 1991). The overall frequency with which all judges placed keywords within the intended theoretical dimension was likewise calculated. A high degree of "correct" placement of keywords within the intended construct could be considered to have a high degree of construct validity, with a high potential for good reliability scores (Moore and Benbasat, 1991).

d. **Results of the first and second sorting rounds.** In the first round, two judges created seven categories, while the other two created six. The inter-judge raw agreement scores averaged 0.79, and kappa scores averaged 0.83 (Table 5). The initial overall placement ratio of keywords within the target dimensions was 86%, with all constructs at or above 89%, except for SV, which was at 63% (Appendix B). This finding indicated that keywords were generally placed as they were intended, and the agreement of MV was 100%. Thus, except for SV, the results demonstrated that dimension scales have construct validity and a high potential for very good reliability coefficients. After the sorting process, each judge independently labeled and defined each of their categories. Then, they met as a group and carried out the same task. Except for SV (which had many ambiguous keywords, e.g., interesting games and videos), the labels and definitions of the independent judges and the panel closely matched those of the original dimensions (Appendix C). Several keywords were identified as being too ambiguous (fitting in more than one category) and were dropped from the keyword pool. A total of 13 keywords were then dropped after the first round.
In the second round, the four new judges were provided the definition of dimensions (Table 4) and asked to sort the remaining keywords based on the definition. Prior to their sorting process,

Table 5
Inter-judge agreements.

Agreement measure	Round 1	Round 2	Round 3	Round 4
Raw agreement	0.72	0.87	0.84	0.78
	0.79	0.77	0.92	0.78
	0.77	0.83	0.92	0.78
	0.84	0.80	0.95	1.00
	0.79	0.87	0.81	0.91
	0.86	0.80	0.81	0.91
			0.84	
			0.89	
			0.89	
			0.92	
Average	**0.79**	**0.82**	**0.88**	**0.86**
Cohen's kappa coefficient	0.81	0.86	0.86	0.87
	0.85	0.84	0.92	0.87
	0.82	0.88	0.94	0.82
	0.85	0.86	0.96	1.00
	0.82	0.90	0.82	0.95
	0.86	0.88	0.86	0.95
			0.86	
			0.90	
			0.92	
			0.94	
Average	**0.83**	**0.87**	**0.90**	**0.91**
Placement ratio summary				
EV	0.97	0.93	0.77	1.00
FV	0.96	0.79	1.00	1.00
MV	1.00	1.00	1.00	0.94
SV	0.63	0.70	0.88	0.75
GV	0.92	1.00	1.00	0.94
DV	0.84	1.00	0.95	1.00
Average	**0.89**	**0.91**	**0.93**	**0.94**

judges were told that they could sort the highly ambiguous keywords into a "doesn't fit" category. The results showed very high agreement among the judges, again with the exception of SV. The raw agreement scores averaged 0.82, and kappa scores averaged 0.87 (Table 5). The overall placement ratio of the keywords within the target dimensions was 90%, with all dimensions at or above 79%, except for SV, which was at 70% (Appendix B). This finding indicated that the keywords were generally placed as they were intended. Thus, except for SV, the results demonstrated that the dimension scales have construct validity and a high potential for very good reliability coefficients.
The analysis of SV indicated that the original construct was quite complex. It has been defined as "the utility derived from the product's ability to enhance social self-concept" (Sweeney and Sourtar, 2001, p. 211) or as "perceived utility acquired from an alternative's association with one or more specific social groups" (Sheth et al., 1991, p. 161), but it also included the idea of "the enjoyment of shopping with friends and family, socializing while shopping and bonding with others while shopping" (Chiu et al., 2014, p.93). The original keywords in SV could be too confusing. In this case, we decided to adopt Sweeney and Soutar's (2001) and Chiu et al.'s (2014) items (Table 4) to revise and extend the keywords. Four keywords identified as either too ambiguous (fitting in more than

one category) or too indeterminate (fitting in no category) were also dropped from the keyword pool in the second round. Three keywords were revised, and an additional four keywords were added to the overall pool. Therefore, at the end of this step, 6 dimensions were identified and 30 keywords remained.

e. **Results of the third sorting round.** The third sorting round was a repeat of the first sorting round. Five employees from different departments of a university were invited as judges. The level of agreement among the judges was quite acceptable. Three judges created six categories, whereas the other two created five. The raw agreement scores averaged 0.88, and kappa score averaged 0.90 (Table 5). Furthermore, 93% of the items were placed within the target dimensions, although some clusters were placed outside the targets (see Appendix B). All labels provided by the judges (Appendix C) to the categories they had created sufficiently reflected the original definition. Thus, no problems could be identified with the construct validity. Furthermore, because the keywords tended to be grouped together once again, their internal consistency remained high. When the keywords that had been placed fairly consistently outside the target dimension were eliminated, 23 keywords remained after the third sorting.
f. **Results of the fourth sorting round.** The aim of the final sorting round was the same as that for the second sorting round. Four new judges were recruited and given the definitions of the dimensions before the sorting process. The subsequent grouping of keywords showed a clear structure. The agreement among the pairs of judges was above 0.86, and kappa scores were also correspondingly high, with an average of 0.91 (Table 5). The overall placement ratio of keywords within the target dimension was 94%, with the lowest score for SV at 75% (Appendix B). The placement of keywords within the target dimensions shows that a high degree of construct validity and potential reliability had been achieved. Hence, six dimensions with construct validity were identified (Table 6). The entire dimension identification procedure is illustrated in Fig. 2.

Finally, after the entire dimension identification procedure finished, six dimensions of MCPV emerged, namely emotional, functional, monetary, guarantee, social, and design value. The analysis of dimension identification answered our RQ1.

3.2. Best–worst scaling design

Best–worst scaling (BWS) is a preference elicitation method (Louviere et al., 2013). It is underpinned by random utility theory, which also underlies discrete choice experiments (Thurstone, 1927). Respondents need to choose the most preferred item (called “most” or “best”) and the least preferred item (“least” or “worst”) in a set of items. Then, the researcher is able to obtain an overall rank of the analyzed items. The first application of BWS was published in 1992 (Finn and Louviere, 1992), which illustrated the “object” case. In the object case, respondents are asked to choose the best and worst from a set of objects (c, Finn and Louviere, 1992). The object case is appropriate when the researcher focuses on the relative values associated with a list of objects (Flynn and Marley, 2007).

Table 6
Results of the fourth sorting round.

Dimensions	Keywords
EV	Match my hobby; feel good; like the account
FV	Helpful; useful; efficient; knowledge
MV	Special offers (e.g., coupons, discounts, and raffles); free gifts; cheap
GV	Good quality; guarantee policies; reliable information
SV	Social approval; interactive with friends
DV	Neat layouts; good display; exquisite pictures

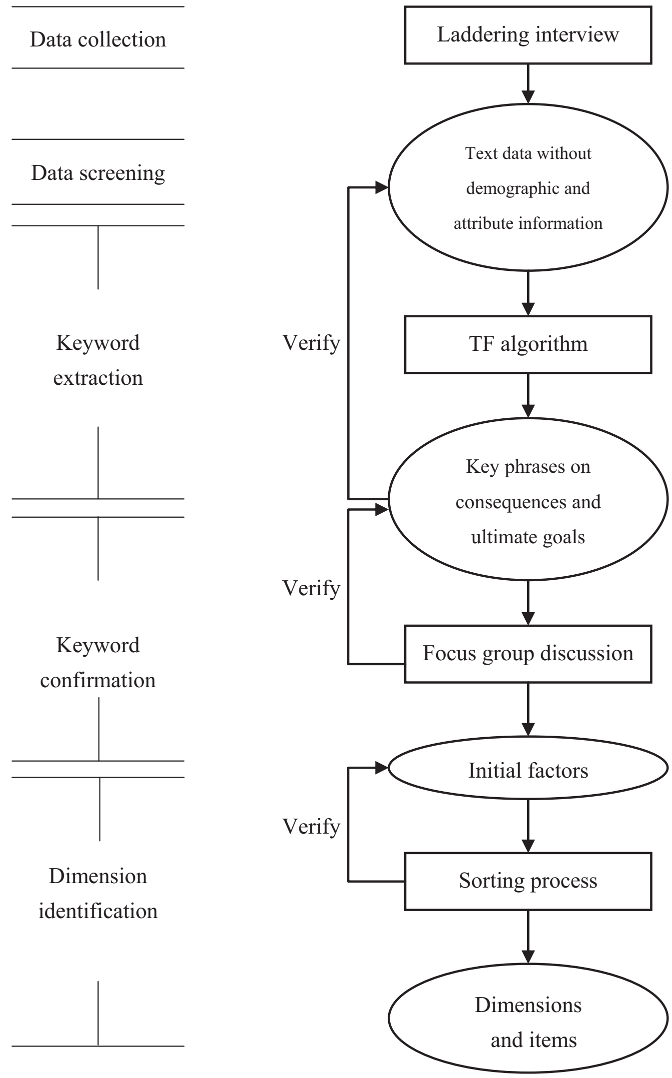

Fig. 2. Dimension identification procedure.

BWS is increasingly used in consumers' preference measurement. Cohen and Neira (2003) indicated that BWS overcomes several biases resulting from scores or ratings. Potoglou et al. (2011) also claimed that BWS has less cognitive burden for respondents than the Likert scale and provides more information than traditional “pick one” tasks asked in discrete choice experiments. BWS has proven its strength for breaking tasks into manageable sizes, thereby reducing the difficulty in ranking the full list of items in terms of their importance or preference (Campbell and Erdem, 2015). BWS has been widely used in social sciences and marketing research (Lee et al., 2008; Louviere and Islam, 2008). Hence, it is an appropriate method for conducting preference measurement studies in consumer behavior.

The first stage in implementing a BWS survey is to choose a statistical design to construct the comparison sets. Although researchers can choose from several statistical designs to construct the comparison sets, BIBD is still a common method (Flynn and Marley, 2007). It does not need to generate whole comparison sets with BIBD. The mathematical properties of BIBD can ensure that occurrence and co-occurrences of objects are constant (Flynn and Marley, 2007). Moreover, Bose (1939) gave a table listing the solutions for various objects. In BIBD, 10 comparison sets are enough for the solution of six objects (Bose, 1939). Louviere et al. (2013) also used BIBD to design the comparison sets and generated 10 sets for a six-object comparison. Thus, we finally created 10 sets for six dimensions based on BIBD.

Table 7
BIBD for the six dimensions.

Set	Value codes	Value names		
1	1 2 5	Design value	Emotional value	Guarantee value
2	2 3 6	Emotional value	Functional value	Social value
3	3 4 2	Functional value	Monetary value	Emotional value
4	4 1 3	Monetary value	Design value	Functional value
5	2 5 4	Emotional value	Guarantee value	Monetary value
6	3 5 6	Functional value	Guarantee value	Social value
7	4 6 5	Monetary value	Social value	Guarantee value
8	1 2 6	Design value	Emotional value	Social value
9	5 1 3	Guarantee value	Design value	Functional value
10	6 4 1	Social value	Monetary value	Design value

Table 8
Illustration survey of BWS task based on Table 7.

Most important	Comparison set 1	Least important
☐	Design value	☐
☐	Emotional value	☐
☐	Guarantee value	☐
Most important	Comparison set 2	Least important
☐	Emotional value	☐
☐	Functional value	☐
☐	Social value	☐
……		
Most important	Comparison set 10	Least important
☐	Social value	☐
☐	Monetary value	☐
☐	Design value	☐

We numbered the six dimensions from 1 to 6 and replaced the same numbers (1–6) in a BIBD table with the corresponding names. A BIBD with six dimensions that creates 10 comparison sets is shown in Table 7. The comparison sets were then embedded into a particular survey format (as displayed in Table 8). Six dimensions were presented in 10 choice sets. Each dimension appeared five times throughout all the series of options (Table 7). Consumers were asked to choose the most and least important dimensions in each set (Table 8).

Best count minus worst count differences (BWS scores) are proven to be sufficient statistics for a conditional (multinomial) logistic regression model (Marley and Louviere, 2005). With a balanced design of BWS experiment, a scale that is approximately 95% as accurate as using multinomial logit to model the same data is provided by simply adding the number of times it is chosen as the best (Auger et al., 2004).

3.3. Data collection

The data were collected through a field survey. This study only focuses on e-business companies that sell tangible products through WeChat official accounts. Before the survey, respondents were shown a campaign of WeChat official account marketing (use Amazon WeChat official account as an example). Respondents were then asked which dimension in each comparison set would be the most/least important factor to affect them in clicking on short titles, clicking on links in an article, and purchasing the products.

The questionnaire included three parts. The first part investigated the most/least important dimension that would affect consumers in clicking one of the title messages to further read the entire article in the first phase (Fig. 1a to 1b). The second part investigated the most/least important dimension that would affect consumers in clicking the product link in the article in the second phase to read detailed information (Fig. 1b to 1c). The third part investigates the most/least important dimension that would affect consumers in eventually purchasing in the third phase (Fig. 1c to 1d). The same 10 comparison sets in all three parts are shown in Table 8.

The data collection for BWS continued from October 2017 to December 2017, and 510 questionnaires were collected. A total of 66 questionnaires were deleted because of a large portion of missing values. Then, we deleted three samples who did not join any WeChat marketing campaign according to the filtering questions. Finally, 441 samples were used for our data analysis. The demographics are summarized in Table 9.

Table 9
Demographic characteristics of participants in the BWS survey.

	Categories	Frequency	Proportion
Gender	Female	205	46.49%
	Male	236	53.51%
Age	Under 18	13	2.94%
	18–25	361	81.86%
	26–35	40	9.07%
	Above 35	27	6.13%
Occupation	Employees	64	14.51%
	Students	365	82.77%
	Others	12	2.72%
Education	High school and below	9	2.04%
	Bachelor	398	90.25%
	Master	30	6.80%
	Others	4	0.91%

4. Analysis and results

4.1. Dimension importance

The best counts, worst counts, and aggregated score of the best-minus-worst differences are shown in Table 10. For example, the best counts of FV was 1136. This finding means that FV was selected as the best for 1136 times in all 10 sets by 441 participants. FV was most often chosen (1136) as the most important (best) and the least often chosen (390) in phase 1; accordingly, its aggregated best − worst score (B − W score) is the highest (Table 10). The mean of individual B − W score (1.692) represents the average B − W score per respondent and is derived by dividing the aggregated B − W score by the sample size (441). The mean B − W score represents the net average of how often an item was chosen as the best or worst. As every dimension appeared 5 times in 10 choice sets, the maximum that could be chosen as the most (best) and least (worst) important is 5; similarly, the minimum individual B − W score is − 5.

The relative importance between dimensions can be easily interpreted when standardizing the B − W score to a probabilistic ratio scale. This ratio scale can be derived by transforming the square root of the best divided by the worst to a 0–100 scale (Mueller et al., 2010). The square root of (B/W) for all dimensions is scaled by a factor, such that the most important dimension with the highest square root of (B/W) is 100. All dimensions can then be compared to one another by their relative ratio, e.g., EV is 0.74 times as important to the overall samples as FV in phase 1 (Table 10).

As shown in Table 10, all the importance measures, i.e., aggregated B-W score, mean of individual B-W score, and standardized square root of (B/W) result are in the same order. For the remainder of this paper, we used the mean of individual B − W score to measure the dimensions. Overall, as shown in Fig. 3, FV is the most important dimension across all the phases. Furthermore, EV is the second most important dimension in phases 1 and 2, whereas GV is the second most important dimension in phase 3. MV had rather similar importance as GV in phases 1 and 2, and then the importance of both increased in phase 3. Furthermore, DV and SV are not very important for consumers.

4.2. Differences of importance

The initial statistics (Table 10) suggested that FV is more important than the other five dimensions in the three phases. However, the

Table 10
Dimension importance on the aggregated level and summary of individual B – W score (n = 441).

Phase	Dimension	Best	Worst	Aggregated B – W score	Mean of individual B – W score	SE of individual B – W score	Sqrt (B/W)	Sqrt stand
Phase 1	FV	1136	390	**746**	**1.692**	2.286	1.707	**100**
	EV	858	532	**326**	**0.739**	2.508	1.270	**74**
	GV	664	637	**27**	**0.061**	2.517	1.021	**60**
	MV	726	800	**− 74**	**− 0.168**	2.812	0.953	**56**
	DV	535	903	**− 368**	**− 0.839**	2.608	0.770	**45**
	SV	491	1148	**− 657**	**− 1.490**	2.583	0.654	**38**
Phase 2	FV	1142	406	**736**	**1.669**	2.345	1.677	**100**
	EV	843	575	**268**	**0.608**	2.551	1.211	**72**
	GV	671	585	**86**	**0.195**	2.451	1.071	**63**
	MV	717	813	**− 96**	**− 0.218**	2.763	0.939	**56**
	DV	505	967	**− 462**	**− 1.048**	2.667	0.723	**43**
	SV	532	1064	**− 532**	**− 1.206**	2.654	0.707	**42**
Phase 3	FV	1101	380	**721**	**1.635**	2.267	1.702	**100**
	GV	837	473	**364**	**0.825**	2.503	1.330	**78**
	MV	846	661	**185**	**0.420**	2.755	1.131	**66**
	EV	696	684	**12**	**0.027**	2.439	1.009	**59**
	SV	498	1115	**− 617**	**− 1.399**	2.557	0.668	**39**
	DV	432	1097	**− 665**	**− 1.508**	2.642	0.628	**37**

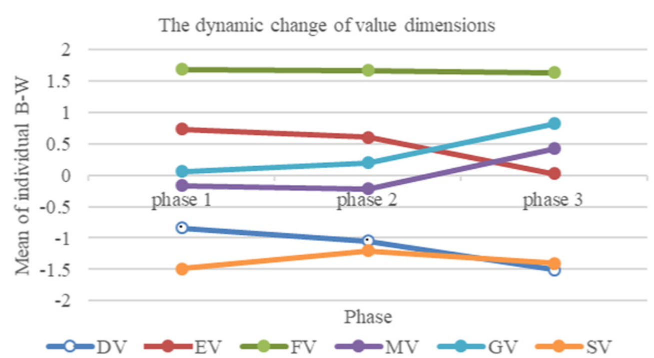

Fig. 3. Dynamic change of value dimensions of MCPV across the three phases.

significance of the differences among the importance of value dimensions still needed to be demonstrated. MANOVA was then conducted to identify whether significant differences exist across the six value dimensions in each phase. Levene's test was conducted and showed that no homogeneity exists in the between-group variance for the three phases ($p < 0.001$). Hence, some adjustments could be undertaken to address the violation of homogeneity in the three phases across the value dimensions, including Brown–Forsythe F or Welch's F statistics. Wilks's lambda [lambda = 0.766, F (15, 7287.76) = 49.226, $p < 0.001$] indicates that a significant multivariate effect exists among the six dimensions in each phase. We found that significant differences exist across six dimensions in each phase [phase 1: F (5, 552.60) = 84.313, $p < 0.001$; phase 2: F (5, 511.69) = 77.176, $p < 0.001$; phase 3: F (5, 685.36) = 107.28, $p < 0.001$]. Problems with the homogeneity of variance exist for the three phases across the six dimensions. Thus, we examined the phases again by using an independent one-way ANOVA with Brown–Forsythe F and Welch's F adjustments.

We confirmed the unadjusted one-way ANOVA outcome [phase 1: F (5, 2640) = 84.313, $p < 0.001$; phase 2: F (5, 2640) = 77.176, $p < 0.001$; phase 3: F (5, 2640) = 107.2843, $p < 0.001$]. The results showed that a highly significant difference still exists across the six dimensions in each phase [phase 1: Welch: F (5, 1231.23) = 92.357, $p < 0.001$; phase 2: Welch: F (5, 1231.239) = 81.899, $p < 0.001$; phase 3: Welch: F (5, 1231.24) = 112.216, $p < 0.001$]. The violation of homogeneity of variance poses no threat to the validity of our results.

As the three phases have six dimensions, post hoc tests were used to explore the source of the significant difference. Each phase did not have equal variances across the value dimensions, which means that the Games–Howell outcome is appropriate. The significant differences across the six dimensions in each phase are as follows.

In phase 1, FV was significantly the most important value dimension than the other five dimensions ($p < 0.001$). EV was more significantly important than DV ($p < 0.001$), MV ($p < 0.001$), GV ($p < 0.01$), and SV ($p < 0.001$). MV was more significantly important than DV ($p < 0.01$) and SV ($p < 0.001$). GV was more significantly important than DV ($p < 0.001$) and SV ($p < 0.001$). DV was more significantly important than SV ($p < 0.01$). In sum, the rank of dimension importance was "FV > EV > GV > MV > DV > SV." However, the difference was not significant between GV and MV ($p > 0.05$).

In phase 2, FV was significantly the most important value dimension than the other five dimensions ($p < 0.001$). EV was more significantly important than DV ($p < 0.001$), MV ($p < 0.001$), and SV ($p < 0.001$). MV was more significantly important than DV ($p < 0.001$) and SV ($p < 0.001$). GV was more significantly important than DV ($p < 0.001$) and SV ($p < 0.001$). In sum, the rank of dimension importance was "FV > EV > GV > MV > DV > SV." However, the differences were not significant between GV and MV, EV and GV, and DV and SV ($p > 0.05$).

In phase 3, FV was significantly the most important value dimension than the other five dimensions ($p < 0.001$). EV was more significantly important than DV ($p < 0.001$) and SV ($p < 0.001$). MV was more significantly important than DV ($p < 0.001$) and SV ($p < 0.001$). GV was more significantly important than DV ($p < 0.001$), EV ($p < 0.001$), and SV ($p < 0.001$). In sum, the rank of dimension importance was "FV > GV > MV > EV > SV > DV." However, the differences were not significant between GV and MV, MV and EV, and SV and DV ($p > 0.05$).

4.3. Gender difference

Studies of gender have indicated that males and females possess different personal traits and societal roles, which are reflected in their perceptions (Goh and Sun, 2014). Thus, independent *t*-tests were conducted to uncover whether a gender difference exists in the preference of each value dimension in the three phases. No significance exists between males and females in evaluating all six value dimensions in phase 1 ($p > 0.05$). No significance exists between males and females in evaluating the importance of the five value dimensions in phase 2 ($p > 0.05$), except for DV. Females perceived less DV than did males in phase 2. Thus, the difference was significant ($p < 0.01$, $t = -2.612$). Except for EV and FV ($p > 0.05$), a significant difference was observed in evaluating the importance of DV ($p < 0.05$, $t = -2.399$), MV ($p < 0.01$, $t = 2.818$), GV ($p < 0.01$, $t = 2.877$), and SV ($p < 0.05$, $t = -2.017$) between females and males in phase 3. Females perceived less DV and SV than did males in phase 3. Females perceived more MV and GV than did males. Thus, the differences were significant.

4.4. Heterogeneity of consumers

We do not yet know if a dimension was similarly important to all consumers from the mean B − W score. For example, the intermediate mean B − W score of GV (0.061) in phase 1 could either be caused by all respondents perceiving it as medium important, or it could be a result of averaging out respondents for whom it was very important with respondents for whom it was not very important. Hence, consumer heterogeneity emerged. Consumer heterogeneity refers to the difference of consumers because some consumers perceive high importance for a dimension, whereas others perceive low importance for the same dimension. Hence, the average alone does not give marketers any guidance related to the issue.

An individual B − W score can be obtained by subtracting the total number of times a respondent chooses a dimension as the least important from the times a respondent chooses it as the most important. The standard deviation of the individual B − W score over all respondents measures the extent to which the importance of the dimension varies over the sample. The greater the standard deviation, the more the respondents differ; some think it is important, whereas some do not. Conversely, the smaller the standard deviation, the more the agreement exists between respondents. At the limit, if the standard deviation is zero, then all respondents agree on the importance and a complete consensus is achieved. That is, the mean gives the average importance. The standard deviation of individual B − W scores gives the variation in the importance of the dimension over the sample, which can be used as the heterogeneity for the dimension importance (Mueller and Rungie, 2009).

In Table 11, all dimensions have a standard deviation above 2. As shown in Fig. 4, GV in phase 2 and EV in phases 2 and 3 showed relatively high agreement of their relative importance, which was indicated by a low standard deviation. MV, DV, and SV had high standard deviations, which indicated a great disagreement and heterogeneity of consumers on dimension importance. Importantly, a maximum agreement (lowest standard deviation) on the importance of FV was found across the three phases among all the respondents.

Most of the consumers presented great difference with the agreement on the importance of MV in the three phases. MV likewise shows a high amount of heterogeneity and reasonable importance. This finding implies that MV is critical to a subset of consumers, even though it may not be important to all consumers. Hence, MV should be paid more attention to, and marketers should respond very differently by targeting those consumers.

Finally, after the analysis of importance of value dimensions finished, the importance of value dimension in different phases of a mobile marketing campaign was demonstrated to be different and change dynamically. The assessment of importance of value dimensions answered our RQ2 and RQ3.

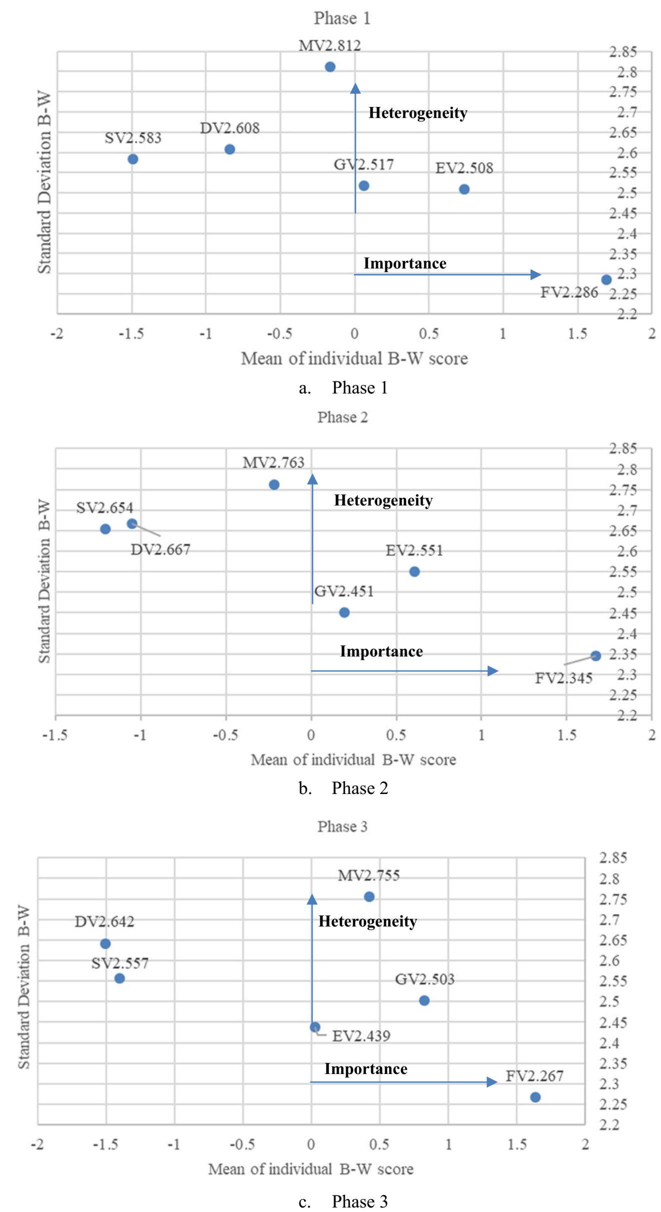

Fig. 4. Dimension importance and heterogeneity.

5. Conclusion

By analyzing the literature and conducting interviews and a rigorous sorting process, we identified the six dimensions of MCPV, namely, DV, EV, FV, MV, GV, and SV. Then, we used the six dimensions as an underlying basis to design a BWS study to discover the varying importance of the dimensions across the three main marketing phases on the WeChat official account.

The majority of consumers were mostly utilitarian, who regarded FV as the most important dimension in all critical phases. Consumers regarded MV, GV, and EV as more important dimensions than DV and SV when they decided to click on short titles, click on links in an article, or purchase products, respectively. EV played a much more important role than MV when consumers just decided to click on short titles or decided to click on links in an article. Moreover, when consumers decided to click on short titles, they regarded EV as a more important dimension than GV, whereas when they decided to purchase products on the official account, GV became more important than EV. DV and SV were not very important across the entire campaign, but the importance of DV was higher than that of SV when consumers decided to click on the short titles.

Moreover, when consumers decided to click on short titles, no significant difference exists between males and females in evaluating all six value dimensions. When consumers decided to click on links in an article to obtain further information, males evaluated DV as more important than did females. When consumers decided to purchase products, males evaluated DV and SV more important than did females, whereas females evaluated MV and GV as more important than did males.

The heterogeneity of consumers was discussed as well. Consumers did not perceive all value dimensions consistently. MV had a high standard deviation, which was regarded as very important for some consumers, whereas some other consumers regarded it as very unimportant. FV had a low standard deviation, which was regarded as the most important value by most consumers.

The identification of new dimensions helps us to understand CPV in the context of mobile marketing. The results show that the importance of value dimensions is significantly different when consumers make their decisions. Furthermore, dimension importance dynamically changes across a mobile marketing campaign. Our findings could make several contributions to academic research and mobile marketing industry.

5.1. Theoretical contribution

We identified six dimensions of MCPV and clarified the varying importance of the value dimensions across a marketing campaign. Gender difference and consumer heterogeneity were also explored. Hence, our theoretical contributions are as follows:

First, the new characteristics of MCPV were explored through a laddering interview and a text-mining analysis of interview data. Compared with typical multidimensional models, we initially proposed a model with six dimensions, namely, DV, EV, FV, MV, GV, and SV. Following this, a rigorous sorting process was conducted to investigate the construct validity of the framework. Although several dimension names were adopted from typical models (e.g., FV from Sheth et al., 1991; EV and SV from Sweeney and Sourtar, 2001), the concept of the dimensions was changed partially in the context of mobile marketing. For example, GV is a dimension that extends the meaning of quality value from Chi and Kilduff (2011). Aside from the quality of products, the reliability of information, guarantee policies, and security issues are also taken into account to reduce the risk when consumers decide to purchase in a mobile campaign. In addition, DV is a new dimension identified in this study. DV refers to the preference and assessment of consumers for design aesthetics and creativity of the campaign, which is related to the personalization feature of mobile advertising (Wu and Hsiao, 2017). Hence, the six-dimension model of MCPV proposed in the current study is different from previous models and fills a gap of studies on mobile marketing.

Second, the dimensions of CPV were investigated in various contexts (Appendix A). However, the varying importance of the dimensions was rarely explored. With the BWS study and MANOVA analysis, we evaluated the varying importance of value dimensions across a mobile marketing campaign. The importance of each dimension dynamically changes in different marketing phases, and the differences are very significant. This study provides a dynamic view for conducting research on CPV through a mobile marketing campaign.

Third, the gender difference in perceiving the importance of each value dimension was identified. Although males and females are different in terms of processing information, our research supplemented the study of gender difference in perceiving value in the mobile marketing field by using information technologies and perceptions (Goh and Sun, 2014).

Finally, we identified consumer heterogeneity in different phases, which means that consumers do not get consistent agreement among all dimension preferences in each phase. Consumer heterogeneity is a critical factor in improving consumer targeting (Mueller and Rungie, 2009). Therefore, this study provides a consumer segment approach that can use the B − W score of CPV as segment criteria.

5.2. Managerial implications

Together with the varying dimension importance across the mobile marketing process, several managerial contributions for marketing managers are presented as follows.

First, for the majority of consumers, FV is always considered the most important dimension in all phases of mobile marketing. Hence, when designing a mobile marketing campaign, marketers should take the utility of their information or products/service into account. For example, the messages released or the products/services sold can help consumers satisfy their practical needs or to improve their time efficiency.

Second, EV is also a significant value dimension, even more important than MV when consumers decide to click short titles or click links in an article for detailed information. However, the importance of EV decreases when consumers decide to finally purchase products, whereas the GV becomes more important than EV. Hence, when marketers design short title messages in phase 1 and compile a detailed article in phase 2, they should try to arouse some consumers' emotional resonance to induce them to click the next page.

Third, the importance of GV and MV is significantly higher than that of DV and SV in all three phases. This finding suggests that marketers should provide consumers some realistic benefits or improve their reliability to better attract consumers to join the campaign, compared with creating a good design or a socializing feature. For example, companies can provide reliable guarantee policies or sufficient after-sale services, such as refund and return policies, or some economic incentives, such as coupons, discounts, and raffles, to induce consumers to make their decisions.

Fourth, most consumers did not assess DV and SV as very critical dimensions when they decided to join a mobile marketing campaign. DV was only more important than SV when consumers decided to click short titles. WeChat official account is one of the most popular mobile marketing channels in China, so the message design has widely accepted norms. Thus, consumers would perceive messages from different WeChat official accounts as similar. Moreover, WeChat is originally a type of social media in China, and the social feature is originally embedded into official accounts. As a result, consumers do not regard SV as a much more important dimension in the campaign.

Fifth, when consumers finally decided to purchase products through a mobile marketing campaign, males perceived DV and SV as more important than did females, whereas females perceived MV and GV as more important than did males. Hence, if marketers focus on male consumers, then they should improve the design aesthetics of advertising and products and add social features into the campaign; if marketers focus more on female consumers, then they should provide benefits, like free gifts, coupons, raffles, and discounts, to facilitate females to purchase their products. They should also provide more guarantee policies and reliable information to convince consumers to make their purchase decision.

Sixth, as for importance heterogeneity, companies should optimize the dimensions with high importance and low heterogeneity, such as FV. Companies should also pay special attention to the dimensions that show a high amount of heterogeneity and reasonable importance (e.g., MV). This finding implies that they are very important to a subset of consumers, even though they may not be important to all consumers. High heterogeneity is suitable for niche markets if the company wants to develop a mixed marketing strategy for small segments of consumers.

To sum up, our study will allow marketing researchers and managers to explore more information from MCPV.

5.3. Limitations and further research

Several limitations are found on our research. First, most of the respondents in our research are aged around 18–25 years old and are university students. Although young groups are the major users of WeChat, various idiosyncrasies between young groups and other groups would lead to different styles of consumer value. Second, we only proved the construct validity of the six-dimension framework by a rigorous sorting process. A further instrument test should be conducted to demonstrate the reliable structure of the framework. Third, although WeChat official account is one of the main mobile marketing channels in China, other different mobile marketing approaches still need to be explored. Our research may not include all types of mobile marketing services. Fourth, several types of WeChat official accounts are found in the WeChat system. We only focused on the official accounts that are owned by e-business companies that sell tangible products. Different types of accounts would influence consumers in different ways, which needs to be further explored.

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Appendix A. Typical multidimensional models

Models	Dimensions and Items	
Two dimensions	Chaudhuri and Holbrook (2002) **1.Utilitarian value** ● I use this product frequently. ● I rely on this product. ● This product is a necessity for me. **2. Hedonic value** ● I love this product. ● I feel good when I use this product. ● This product is a luxury for me.	Chiu et al. (2014) **1. Utilitarian value** ● Product offerings ● Product information ● Monetary saving ● Convenience **2. Hedonic value** ● Adventure ● Gratification ● Role ● Best deal ● Social ● Idea
Four dimensions	**Sweeney and Sourtar, 2001** **1. Emotional value** ● Is one that I would enjoy ● Would make me want to use it ● Is one that I would feel relaxed about using ● Would make me feel good ● Would give me pleasure **2. Social value** ● Would help me to feel accepted ● Would improve the way I am perceived ● Would make a good impression on other people ● Would give its owner social approval **3. Functional value (performance/quality)** ● Has consistent quality ● Is well made ● Has an acceptable standard of quality ● Has poor workmanship ● Would not last a long time ● Would perform consistently **4. Functional value (price/value for money)** ● Is reasonably priced ● Offers value for money ● Is a good product for the price ● Would be economical	Chi and Kilduff (2011) **1. Emotional value** ● Is one that I would enjoy ● Is one that I would feel relaxed about using ● Would make me feel good ● Would give me pleasure **2. Social value** ● Would help me to feel accepted ● Would improve the way I am perceived ● Would make a good impression on other people ● Would give its owner social approval **3. Quality value** ● Has consistent quality ● It is well made ● Has an acceptable standard of quality ● Would perform consistently **4. Price value** ● Is reasonably priced ● Offers value for money ● Is a good product for the price ● Would be economical
Five dimensions	Sheth et al. (1991) 1. **Conditional value** ● Have seasonal value ● Be associated with "once in a lifetime" events ● Be used only in emergency situations ● Have more subtle conditional associations 2. **Social value** ● Highly visible products ● Goods or services to be shared with others ● Functional or utilitarian products 3. **Emotional value** ● Goods and services ● Esthetic alternatives ● More tangible and seemingly utilitarian products 4. **Functional value** Derived from its characteristics or attributes such as ● Reliability ● Durability ● Price 5. **Epistemic value** ● Entirely new experiences ● An alternative that provides a simple change of pace	Williams and Soutar (2009) 1. **Value for money** ● Good return for money ● Value for money ● Good one for the price paid ● Reasonably priced 2. **Social value** ● Gives social approval from others ● Makes me feel accepted to others ● Improves the way a person is perceived ● Give a good impression on other people 3. **Emotional value** ● Gave me feelings of well-being ● Was exciting ● Made me elated ● Made me feel happy 4. **Functional value** ● Consistent quality ● Done well ● Acceptable standard of quality ● Well organized 5. **Epistemic value** ● Made me feel adventurous ● Satisfied my curiosity ● Was an authentic experience ● We did a lot of things on the tour

Appendix B. Keyword placement ratio

see Tables B1–B4

Table B.1
First sorting round.

Target category	Actual category							TOT	TAG %
	EV	FV	MV	SV	GV	DV	N/A		
EV	31			1				32	97
FV		27			1			28	96
MV			16					16	100
SV				25	1	10	4	40	63
GV				1	22	1		24	92
DV						27	5	32	84
Total item placement:172			Hits:148 overall hit ratio:86%						

Table B.2
Second sorting round.

Target category	Actual category							TOT	TAG %
	EV	FV	MV	SV	GV	DV	N/A		
EV	26	1		1				28	93
FV		19	3	1	1			24	79
MV			16					16	100
SV	2	1	1	14		1	1	20	70
GV					16			16	100
DV						16		16	100
Total item placement:120			Hits:107 overall hit ratio:89%						

Table B.3
Third sorting round.

Target category	Actual category							TOT	TAG %
	EV	FV	MV	SV	GV	DV	N/A		
EV	23	4			2		1	30	77
FV		20						20	100
MV			20					20	100
SV	1	3		35			1	40	88
GV					20			20	100
DV					1	19		20	95
Total item placement:150			Hits:137 overall hit ratio:91%						

Table B.4
Fourth sorting round.

Target category	Actual category							TOT	TAG %
	EV	FV	MV	SV	GV	DV	N/A		
EV	12							12	100
FV		16						16	100
MV	1		15					16	94
SV	5			15				20	75
GV				1	15			16	94
DV						12		12	100
Total item placement:92			Hits:85 overall hit ratio:92%						

Appendix C. Judges' labels for categories

see Tables C1–C4

Table C.1
First sorting round: Individual judge's construct labels.

	Judges			
Constructs	A	B	C	D
EV	Feeling	Emotion	Feeling	Emotion
FV	Utility	Function	Utility	Utility
MV	Price	Price	Price advantage	Promotion
SV	Marketing campaign	Third-party views	Third-party comments	Third-party
GV	Creditability	Reliability	Safety	Guarantee
DV	Design	Design	Attractiveness of promotion	Design
N/A	Content			Entertainment

Table C.2
Second sorting round: Panel's labels and definitions.

Labels	Definitions
EV	Consumers' preference and assessment for the extent of various content and services in this mobile marketing campaign which satisfy their emotion requirement.
FV	Consumers' preference and assessment for the extent of products or services in this mobile marketing campaign which satisfy their practical needs or improve their task efficiency.
MV	Consumers' preference and assessment for price and promotions in this mobile marketing campaign.
GV	Consumers' preference and assessment for the extent of reduction of risk in this mobile marketing campaign.
SV	Consumers' preference and assessment for interactivity and social identity when they participate in this mobile marketing campaign.
DV	Consumers' preference and assessment for design aesthetics and creativity of this mobile marketing campaign.

Table C.3
Third sorting round: Individual judge's construct labels.

	Judges				
Constructs	A	B	C	D	E
EV	Feeling	Impression	Like	Hobby	Feeling
FV	Utilitarian	Influence	Usefulness	Work and study	Knowledge
MV	Marketing	Product	Promotion	Shopping	Price
SV	Socializing	Social goals	Interactivity	Marketing	Socializing
GV	Brand	Brand image	Functionality	Shopping	Product quality
DV	Feeling	Impression	Layout design	Design aesthetics	Design quality
N/A				News & comments	

Table C.4
Fourth sorting round: Final results.

Dimensions	Keywords
EV	Match my hobby; feel good; like the account
FV	Helpful; useful; efficient; knowledge
MV	Special offers (e.g., coupons, discounts, raffles); free gifts; cheap
GV	Good quality; guarantee policies; reliable information
SV	Social approval; interactive with friends
DV	Neat layouts; good display; exquisite pictures

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