**Do customers using iOS vs Android handsets in retail shopping differ in their customer value?**

**Abstract**

As retail marketing literature increasingly focuses on media engagement and customer value creation, there has been growing interest in mobile commerce (MC) research. One area of investigation is how customers use internet-enabled mobile devices to interact with retailers and gain value. This study explores the role of the operating system (OS) of customer handsets in MC, specifically in the context of Fast Moving Consumer Goods (FMCG) retail buying. Through two studies, we examine how differences in OS relate to distinctive customer values. In Study 1, we surveyed 398 customers and found that the customer handset OS moderates the influences of social media and traditional media engagement, as well as the impacts of retail 'place' on customer value. Study 2 used a dataset from a real foreign FMCG brand that actively leverages Chinese local social media platforms such as WeChat and Weibo as its main social media engagement mechanisms, and analyzed how such engagement moderates the impact of 'place' on actual product sales across both e-commerce and traditional retail channels. The findings offer important theoretical contributions to customer value in MC, and have implications for marketers to use customer's handset OS as a useful targeting and segmentation tool.

**Keywords**

*Social media, customer value, mobile commerce, generalized structured component analysis, partial least squares.*

**Introduction**

With the enormous growth of mobile internet users on a global scale, one emerging trend amongst e-marketers is to use consumer’s mobile operation system (OS) as a new targeting variable. According to Statista (2021), over 920 million mobile internet users in 2020 and the numbers expected to be surpassed one billion by 2022 in China for example. With such a huge user base, academics and practitioners are intrigued to explore the specific behavior of mobile internet users (Chang et al., 2017; Wan et al., 2017; Wong et al., 2019). One critical area of interest is exploring the relationship between mobile operating systems and customer value, particularly for iOS and Android users. Extant literature on the behavior of mobile internet users (including but not limited to, their motivations, and purchase intention) seem to dominate, yet they do so with an aggregate knowledge which disregards the diversity therein. More importantly, with the increasing empirical evidence showing the divergent Android and iOS user behavior, and ultimately their customer value, a gap exits on how their engagement of traditional and social media vary and how such differences would impact on their customer value.

From a theoretical perspective, this inquiry is also important. First, customer purchasing behavior and process in the retail sector is always a focal point of retail research interest. With the increasing development of advanced information-technology (IT) consumers retail buying process is suggested to follow a process view instead of a point-in-time view (Johansson, 2001). The ethos of the process view of retail buying is that consumers leverage the IT technology to source, use of information and interact with retailers as suppliers over the long-run. There is no exception with the fast-upgrading powerful smartphone devices (both in hardware and software), where at their fingertips, customers actively search, compare, inquire product information, redeem coupons, make digital payments, and sometimes lodge complaints and disseminate their buying experiences to social media. In sum, customers are actively involving in value creation process in retail buying. Not only has this access to IT closed the gap between physical shops with online offerings (Brynjolfsson, Hu, and Rahman 2013), but also it creates more social media experiences that contribute to relationship building with the retailers (Rapp, et al., 2013). Second, from the supply side, and the perspective of omni-channel retailing, it aims to provide a seamless cross channel buying experience where heterogeneity in customers is more likely to be addressed and met (Yrjölä, et al., 2018). Such development of multi-channel touchpoints increases the likelihood customer forge deeper relationships with the retailer, and ultimately contributing to customer value. Therefore, when resources on supply and demand side putting together, informed by the service-dominant logic (Vargo and Lusch 2004, 2008) amongst other relevant theories, values are co-created.

Mobile operating systems play a critical role in the relationship between various marketing stimuli (such as price promotions and place), and customer media engagement (such as social media and traditional media) with customer value. Understanding how these stimuli and media channels affect customer value can provide valuable insights for businesses in creating and implementing effective marketing strategies. For instance, previous research suggests that iOS users tend to have higher education and income levels and are more likely to prioritize design and user experience when making purchase decisions, while Android users may be more value-oriented and price-sensitive, and may engage in more research and comparison shopping before making a purchase.

Despite the importance of this topic, there is still a significant research gap in terms of understanding the relationship between mobile operating systems and customer value in the retail shopping context. This paper aims to fill this gap by exploring the differences in customer value perceptions and behaviors between iOS and Android users when shopping online. Specifically, we investigate how operating system preferences may affect customers' attitudes towards different elements of the online shopping experience. With these in mind, this study puts forward a research framework where we integrate customer value creation into a structure where it is informed by both marketing stimuli (in particular the price promotions, and marketing ‘place’ element) as well as customer media engagement with traditional as well as social media. Then, we examine whether customer’s use of smartphones with varying OS serve as an important marketing segmentation tool in discerning varying levels of customer value.

The paper is structured as follows: First, we provide a review of the relevant literature on mobile operating systems and customer value, highlighting the key research gaps and questions. We then describe the methodology used in our study, including the sample selection process, data collection procedures, and statistical analyses. Next, we present our findings, discussing the differences in customer value perceptions and behaviors between iOS and Android users in the retail shopping context. Finally, we conclude the paper with a discussion of the implications of our findings for businesses and future research directions.

**Conceptual development and hypotheses**

It has been reported widely that consumer behavior of iOS and Android mobile users were different because of various social-economic factors (Zimba et al., 2017; Gotz et al., 2017). Existing literature indicates that various psychographics factors (e.g. motivations, beliefs, and priorities) and demographics factors (e.g. age, location, occupation) are differentiating the usage of iOS and Android from the consumer behavior perspectives. For instance, researchers have found Android users were cautious of security and privacy issues than iOS users who care less (Benenson et al., 2013). Other studies argue factors such as the effect of gender and age (Gerpott et al., 2013); technology enthusiasts (Benhardus and Kalita, 2013) can be useful sources of information for marketers to design their marketing strategies accordingly. Therefore, recognizing this targeting strategy can be justified on the assumption that mobile iOS research is important to create relationships among customer value and media engagements. In this study, we attempt to uncover how shoppers on different iOS would exhibit their media usage (traditional and social media), and how they react to e-tailers’ price promotions and their channel experiences-which ultimately drive their customer value.

In marketing literature, for example, situated in US retail banking context, study shows that social media usage influenced co-creation behaviours through the mediators of trust, customer engagement and participation attitude (Lars-Erik & Park, 2021); Similarly, other study argues that engagement with brands on social media build consumer brand trust, although social media brand engagement per se does not directly drive customer purchase intention (Osei-Frimpong, et al., 2022). Actually, leveraging on the power of social media engagement, firms are increasingly and strategically designing social media engagement initiatives surrounding customers' experiential interaction events therefore to influence the sentiment of customers' digital engagement (Meire, et al., 2019). In Information Systems (IS) literature, studies show pre-consumption customer engagement using social media creates business value by improving product purchase performance (i.e. movies) (Castillo, et al., 2021).

In cyber-psychology, extant empirical studies on social media engagement has associated it with more negative outcomes such as lower self-esteem, where the latter is seen as an instrumental psychological variable for social interactions ([Gonzales & Hancock, 2011](https://eds-p-ebscohost-com.ez.xjtlu.edu.cn/eds/detail/detail?vid=0&sid=29dd0108-b484-4710-82be-d7bb4e643d35%40redis&bdata=JnNpdGU9ZWRzLWxpdmUmc2NvcGU9c2l0ZQ%3d%3d#c11); [Hanna et al., 2017](https://eds-p-ebscohost-com.ez.xjtlu.edu.cn/eds/detail/detail?vid=0&sid=29dd0108-b484-4710-82be-d7bb4e643d35%40redis&bdata=JnNpdGU9ZWRzLWxpdmUmc2NvcGU9c2l0ZQ%3d%3d#c13); [Woods & Scott, 2016](https://eds-p-ebscohost-com.ez.xjtlu.edu.cn/eds/detail/detail?vid=0&sid=29dd0108-b484-4710-82be-d7bb4e643d35%40redis&bdata=JnNpdGU9ZWRzLWxpdmUmc2NvcGU9c2l0ZQ%3d%3d#c37)). Social interaction is core to customer engagement and firm financial performances (Meire, et al., 2019), so lower self-esteem may result in less consumptions. However, there are competing findings here. For example, a study from Gotz, et al., (2017) argue that as far as psychological differences such as personality is concerned, there exits extremely noticeable differences between users on iOS compared with Android. However, another study conducted over a more diversified global sample e.g. US, Asia and Europe finds that iPhone users are behaviorally more compassionate and altruistic than Android users (Anand, et al., 2021). More practical-led market research however simply reports that from an economic perspective, Apple iPhone users are financially more superior -with a median income of $85,000 back in 2014 alone, or 40 percent higher - than those with Android devices (Schick, 2014).

As far as technically operation system is concerned, app developers usually design an app for either not both, where in general, Android operating system is open-source, and therefore more relax towards third-party developers (nevertheless, more vulnerable to virus risks) whilst iOS applies more closed system and applied restrictions over external non-verified apps and iOS does not port its apps to Android. These barriers of operating system for smartphone devices typically result into this dichotomy. Also, with the rapid development of smartphone as a dominant mobile payment method because of easiness and security, it has important impact on retailers (Kent, 2012).

Our operationsliation of traditional media in the context of retailing, uses the following five variables which are well-supported in marketing and retailing literature. They are: TV advertising, magazine, newspaper (Breyer, 1949), referrals (Brown, et al., 1987; Wilson, 1994; Schmitt, et al., 2011), in-store promotion (Walters & Rinne, 1986; Kumar & Leone, 1988). Through communicating values to customers, traditional media offers stimuli to customers, in ways such as visual, audio, touch (Peck & Shu,2009) of the product in retail stores, to elicit customer sensory (Krishna, 2012) and/or emotional arousal or interests in the product offerings. Referrals, depends on the strengths of relational ties between the WOM giver and receiver, would can be influential in receiver’s decision making in purchases (Brown, et al., 1987). Recent studies of the benefit of the traditional physical store in today’s multi-channel buying environment, is that the onsite in-store engagement of the customer with products and in particular high-value products enables customers to better inspect ‘deep’ products through the mechanism of experiential learning, and making informed decisions, therefore and eventually contributing to higher customer values (Zhang, et al., 2022).

With the proliferation of smartphones, on one hand it is seen as a substitution of traditional media (in particular relating to product search stage) (Singh, & Jang, 2022), but arguably, can also been seen a facilitation of traditional media messages to be shared, disseminated widely to a larger community in a faster speed. For example, a challenge for traditional media communication to direct commercial messages is that it can be less effective in targeting at the right segmentation. However, nowadays with technology advancement in mobile marketing, TV ads can be programmatic, in that it direct commercial messages to the right audience based on their prior search and display ads (Malthouse, et al., 2018). In addition, more advanced technology such as augmented reality devices can engage customers better in communicating their brand value (Tan, et al, 2022). This is consistent with literature in customer experience and customer journey (Lemon & Verhoef, 2016).

Given these, we would argue that (1) customers on iOS may come from a more affluent social segment with less price sensitivity over consumption, therefore it strengthens the relationship between traditional media engagement (as measured by five indicators in this study) on their customer value, whilst Android weaken this relationship; similarly, from an economic perspective, it is reasonable to propose that (2) customers on iOS may strengthen the relationship between social media engagement on their customer value, whilst Android less so. Given this mixed results, we do not hypotheses the valence on the impacts on the aforementioned relationships but postulate below two hypotheses:

**H1: Customer’s operating system of their online shopping handset moderates the impact of customer’s traditional media engagement on customer value.**

**H2: Customer’s operating system of their online shopping handset moderates** **the impact of customer’s social media engagement on customer value.**

**Fig 1. Research Model**

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Source: authors own

The current retail landscape is characterized by dynamic shopping behaviors across both online and offline channels, and therefore, retailers cannot overlook the significance of channel and price promotions. According to a recent study by Zhang et al. (2022), multi-channel retailers need to make informed decisions regarding the right product/channel combination to enhance customer value. From a customer's perspective, the choice of channel for shopping is a dynamic decision-making process that evolves over time and has a significant impact on the customer's shopping journey and lifetime value. As customers progress from the trial stage to the post-trial stage, their shopping channel preferences may change, making effective multichannel management crucial for maximizing customer value (Valentini et al., 2011). Classic retail channel for the customer can be supermarket (Slack, et al, 2020), convenience store (Wood, & Browne, 2007), department store (Achabal, et al., 1990), specialist store (Maesen, & Lamey, 2023), big name e-tailer (Kalaignanam, et al., 2018), and overseas purchase (Tu, 2020).

Relevant literature shows that customer’s final purchase channel is a result of their perception of channels across mobile devices, desktop computers or in-store. This would in turn influence their shopping satisfaction (Singh, & Jang, 2022). Furthermore, experiments have shown that consumers who make purchases on their smartphones tend to prefer more unique and self-expressive options compared to those who make purchases on desktop computers, as smartphones are perceived as more personal (Song & Sela, 2022).. Taking a broader perspective, the medium of a customer's online shopping terminal and their activities, such as searching and buying, across different operating systems, could all have varying impacts on their online purchasing decisions (Orimoloye et al., 2022). Based on the assumption that different mobile operating systems may have unique features and capabilities that influence the way customers interact with marketing channels and their perception of value. For instance, customers using iOS may have a different online shopping behavior than those using Android, and therefore, the effect of marketing channels on their value may differ, we posit:

**H3: Customer’s operating system of their online shopping handset moderates the impact of marketing ‘place’ (channel) on customer value.**

Another important factor for customer shopping online is price incentive. Price promotion in general increases consumers' perceived resources (Zhang, et al., 2021). Research shows that there can be a bigger price dispersion online than offline depending on the retailer type and shopping risks (Zhuang, et al., 2018). Communicating values through pricing strategy has been at the core of marketing and retail research. In this study, we operationalise price promotion using eight commonly retailer-deployed strategies: buy-one-get-one-(for-free) (i.e. BOGO or BOGOF) (Wu, & Honhon, 2022), and its variations such as “free for extra purchased items (extra-free)” or “Buy and get one or more items for free or on discount. Or, “spend and get one or more items for free or on discount”, “member’s price”, “exchange points or earn loyalty points” (e.g. “buy and earn loyalty”; or simply “spend and earn loyalty”), “conditional promotion/discounts” (e.g. “buy and save off the entire sale”; “buy and save off specific items”; or simply, “buy and pay a fixed price”), “prize draw”, “coupon redemption”, “straight (unconditional) discounts”.

Base on the literature, customers who use iOS mobile operating systems might show a stronger positive relationship between price promotions and their perceived value than those who use Android mobile operating systems. This is based on the premise that iOS users have a higher socio-economic status, and therefore, may be more sensitive to price promotions and perceive greater value when shopping online. On the other hand, Android users may be more focused on the functional aspects of their devices and less influenced by price promotions. Thus, this study seeks to contribute to the understanding of how mobile operating systems influence consumer behavior in the context of online shopping and provide practical implications for marketers and retailers to optimize their promotional strategies based on the mobile operating system used by their target customers. Based on these, and also aforementioned discussions on iPhone vs. Android users differences, we posit:

**H4: Customer’s operating system of their online shopping handset moderates the impact of marketing ‘price promotion’ on customer value.**

**Study 1**

**Design and sample**

The dataset was part of a dissertation project on a senior executive degree course at a major British business school in 2017. The objective of the original study was to sample consumers’ purchase behavior for a real branded FMCG product across major cities in China. The original project was granted by the institutional ethics committee. The questionnaire was administrated by a professional third-party market research platform with the function of automatic switch of language between Chinese and English when participants were allow to make a choice. The accuracy of translation was verified with joint efforts by the project group and the research company.

The participant firm wished to remain anonymous. Altogether, we extracted 398 fully completed questionnaires for the purposes for this study-amongst which the participants identified themselves as one of the two mainstream operating systems i.e. iPhone user for conducting their regular online shopping ($N\_{iOS}$=241) and their counterpart shoppers who use Android devices ($N\_{Andriod}$ =157).

We also created a five latent variables and link measured data to support them. Specifically, traditional media engagement is measured by five reflective indicators using “TV advertising”, “magazine”, “referrals”, “in-store promotion”, and “newspaper”. Social media engagement is measured by three reflective indicators using “online forum”, “mobile-based social media”, and “PC-based social media”. Price promotion is measured by eight reflective indicators using “buy-one-get-one-for-free (i.e. BOGOF)”, “free for extra purchased items (extra-free)”, “member’s price”, “exchange points”, “conditional discounts”, “prize draw”, “coupon redemption”, “straight (unconditional) discounts”. The place (marketing channel factor) is measured by six reflective indicators using “supermarket”, “convenience store”, “department store” (Achabal, et al., 1990), “specialist store”, “big name e-tailer”, and “overseas purchase”. Customer value is the product of customer spending with their purchase frequency on yearly basis. Control variables are customer’s age group, level of education, tier of cities, gender, and monthly salary range.

*Demographics of the sample*

Our sample overall has over 70% female respondents and has more than 60% iPhone users ($N\_{total}$ = 398, 71.4% female, 28.6% male, $M\_{Age Group}=3.14, SD=0.84, SE=0.04.$ $N\_{iOS}$ = 241, 60.5% vs. $N\_{Android}=$157, 39.4%). Over 95% of our sample are consumers in the age group 25-40, more specifically, 22.4% (25-30 years old age band), 44.2% (30-35) and 29.1% (35-40), with remaining 0.5% for people under 25 years old, and 3.3% for older than 40-45 age range. They were in general highly educated (PG: 23.4%; UG: 64.3%; middle school: 1.3%, and high school: 11.1%). 47.7% identified themselves living in Chinese tier 1 cities, and 42% tier 2. The other (lower) tier city dwellers were 10.3%. Nearly half of the respondents had monthly salary above 5000 RMB, with 29.9% (5001-8000 RMB) and 16.8% for even higher salary i.e. 8001-12000RMB. At the tail area, there were 15.1% salary earner accessing 12001-20000 RMB monthly. Then the respondents with salary from 20001-30000RMB counted for 7.3%, 30001-40000RMB counted for 3.5% and lastly, salary over 40000RMB only 5%.

iPhone respondents were on higher monthly salary band: $M\_{iOS}$=4.99, SD = 1.86, SE = 0.12 vs. $M\_{Andriod}$= 4.43, SD = 1.60, SE = 0.12, F (1, 396) = 9.515, p=.002). Android handset shoppers have higher frequency of order ($M\_{iOS}$= 3.31, SD = 1.19, SE = 0.07 vs. $M\_{Andriod}$= 3.63, SD = 1.29, SE = 0.10, F (1, 396) = 6.34, p=.012) but there no difference is their customer values ($M\_{iOS}$= 12.92, SD = 6.80, SE = 0.43 vs. $M\_{Andriod}$= 13.80, SD = 7.42, SE = 0.59, F (1, 396) = 1.47, p=.225 [n.s.])[[1]](#footnote-1).

*Customer media engagement of the sample.* Respondents on iPhone have more exposure to TV advertising ($M\_{iOS}$= 3.02, SD = 1.57, SE = 0.10 vs. $M\_{Andriod}$= 3.37, SD = 1.29, SE = 0.10, F (1, 396) = 8.20, p=.004) and newspaper ($M\_{iOS}$= 4.03, SD = 1.37, SE = 0.08 vs. $M\_{Andriod}$= 3.63, SD = 1.49, SE = 0.12, F (1, 396) = 7.45, p=.007). Android users however, engaged with retailer’s in-store promotion media stronger: ($M\_{iOS}$= 2.78, SD = 1.69, SE = 0.10 vs. $M\_{Andriod}$= 3.29, SD = 1.65, SE = 0.13, F (1, 396) = 9.04, p=.003).

*Price promotion and place.* Android handset users engaged channels more heavily withsupermarket: ($M\_{iOS}$= 2.78, SD = 1.69, SE = 0.10 vs. $M\_{Andriod}$= 3.29, SD = 1.65, SE = 0.13, F (1, 396) = 9.04, p=.003) as well as convenience store: ($M\_{iOS}$= 1.55, SD = 1.12, SE = 0.07 vs. $M\_{Andriod}$= 2.08, SD = 1.47, SE = 0.11, F (1, 396) = 16.22, p=.000). In contrast, iPhone handset users engaged more heavily with buying from overseas purchasers: ($M\_{iOS}$= 2.96, SD = 1.75, SE = 0.11 vs. $M\_{Andriod}$= 2.39, SD = 1.60, SE = 0.12, F (1, 396) = 10.69, p=.001), as well as acquiring through channels from top brands carrying retailers: ($M\_{iOS}$= 0.44, SD = 0.49, SE = 0.03 vs. $M\_{Andriod}$= 0.22, SD = 0.41, SE = 0.03, F (1, 396) = 21.81, p=.000).

**Data analyses**

We employed Generalized Structured Component Analysis (GSCA) to analyses our structural model. Difference in online shopper’s main device OS i.e. iPhone and Android was used as criteria for multi-group analysis. We chose GSCA was mainly due to researchers’ preferences in running multi-group analyses in GSCA and the benefit that GSCA can overcome the non-normality assumption. Another justification is that our measurements were mainly designed to reflect more closely with practice, instead of using more traditional literature-based measurement scales. In this way, GSCA accommodates better with our use of “soft modelling”.

Results show that OS does moderate the impact of customer traditional media engagement on their customer value, where iOS positively moderates this relationship (β= 0.19\*\*); but their Android counterparts negatively moderated this relationship (β= -0.40\*\*). Therefore, H1 is supported. Further, for the effect of social media engagement on customer value, we find that iOS negatively moderated this relationship (β= -0.22\*\*) whist Android counterparts has a non-significant moderation impact. H2 therefore is partially supported.

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From the marketing mix management perspective as far as place and price promotions is concerned, H3 is not supported, where both iOS and Android users have a positive significant impact on this hypothesized relationship with β values 0.34\*\* and 0.53\*\*. However, for the hypothesized moderation effect on price promotion on customer value, we find partial support. The Android group strongly and negatively moderate this relationship (β= -0.12\*\*) whilst there are no statistical significant effect from iOS group. To this end, H4 is partially supported. In Tables below, we report detailed multi-group analyses results and structural equation modelling results.

**Table 1. Model fit of the result**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 　 | Measure | Std.Error | 95%CI\_LB | 95%CI\_UB |
| FIT | 0.39 | 0.01 | 0.38 | 0.42 |
| AFIT | 0.39 | 0.01 | 0.37 | 0.41 |
| GFI | 0.99 | 0 | 0.98 | 0.99 |
| SRMR | 0.15 | 0.01 | 0.14 | 0.17 |
| FIT\_M | 0.47 | 0.01 | 0.45 | 0.5 |
| FIT\_S | 0.05 | 0.01 | 0.04 | 0.07 |

AFIT = Adjusted FIT; SRMR= Standardized Root Mean Square;

**Table 2. Parameter Estimates of Loadings (Multi-group)**

|  |  |  |
| --- | --- | --- |
|   | **Group 1 [OS = iPhone ]** | **Group 2 [ OS = Android ]** |
|   | Estimate | Std. Error | 95%CI\_LB | 95%CI\_UB | Estimate | Std. Error | 95%CI\_LB | 95%CI\_UB |
| TV\_AD | 0.54 | 0.09 | 0.35 | 0.68 | 0.78 | 0.05 | 0.65 | 0.83 |
| REFERRALS | 0.83 | 0.03 | 0.76 | 0.88 | 0.85 | 0.03 | 0.77 | 0.90 |
| MAGAZINES | 0.74 | 0.05 | 0.63 | 0.81 | 0.56 | 0.10 | 0.37 | 0.70 |
| NEWSPAPER | 0.48 | 0.08 | 0.28 | 0.60 | 0.66 | 0.09 | 0.42 | 0.79 |
| IN\_STORE\_PROM | 0.2081[n.s] | 0.15 | -0.11 | 0.47 | 0.01[n.s] | 0.17 | -0.36 | 0.40 |
| FORUM | 0.79 | 0.03 | 0.72 | 0.84 | 0.78 | 0.04 | 0.69 | 0.83 |
| WECHAT | 0.89 | 0.02 | 0.86 | 0.92 | 0.87 | 0.03 | 0.81 | 0.92 |
| WEIBO | 0.78 | 0.04 | 0.70 | 0.84 | 0.85 | 0.03 | 0.78 | 0.90 |
| CUST\_VALUE | 1.00 | 0.00 | 1.00 | 1.00 | 1.00 | 0.00 | 1.00 | 1.00 |
| SUPERMARKET | 0.70 | 0.05 | 0.61 | 0.77 | 0.81 | 0.03 | 0.74 | 0.85 |
| CONV\_STORE | 0.71 | 0.04 | 0.63 | 0.78 | 0.78 | 0.04 | 0.69 | 0.85 |
| DEPT\_STORE | 0.60 | 0.08 | 0.44 | 0.72 | 0.48 | 0.12 | 0.25 | 0.67 |
| SPECIALIST\_STORE | 0.68 | 0.04 | 0.60 | 0.74 | 0.73 | 0.05 | 0.59 | 0.82 |
| BIG\_NAME\_E\_TAILER | -0.43 | 0.10 | -0.59 | -0.20 | -0.44 | 0.11 | -0.59 | -0.16 |
| OVERSEAS | -0.1931[n.s] | 0.13 | -0.44 | 0.17 | -0.2279 [n.s] | 0.16 | -0.50 | 0.03 |
| PROM\_BOGOF | 0.70 | 0.04 | 0.62 | 0.78 | 0.35 | 0.12 | 0.06 | 0.55 |
| PROM\_EXTRA\_FREE | 0.64 | 0.04 | 0.53 | 0.72 | 0.37 | 0.11 | 0.10 | 0.59 |
| PROM\_MEBER\_PRICE | 0.72 | 0.05 | 0.60 | 0.79 | 0.77 | 0.03 | 0.70 | 0.82 |
| PROM\_POINTS\_EXCH | 0.80 | 0.03 | 0.75 | 0.84 | 0.87 | 0.02 | 0.83 | 0.91 |
| PROM\_CONDITIONAL\_DISC | 0.76 | 0.03 | 0.69 | 0.82 | 0.59 | 0.07 | 0.43 | 0.70 |
| PROM\_PRIZE\_DRAW | 0.76 | 0.03 | 0.69 | 0.80 | 0.81 | 0.04 | 0.72 | 0.87 |
| PROM\_COUPON | 0.69 | 0.04 | 0.59 | 0.75 | 0.82 | 0.03 | 0.74 | 0.88 |
| PROM\_STRAIGHT\_DISCOUNT | 0.43 | 0.07 | 0.29 | 0.55 | 0.24 | 0.11 | -0.04 | 0.42 |

**Table 3. Parameter Estimates of Path Coefficients**

|  |  |  |
| --- | --- | --- |
|  | **Group 1 [OS = iPhone]:** | **Group 2 [OS = Android]:** |
| **Hypothesized Relationships**  | Estimate | Std.Error | 95%CI\_LB | 95%CI\_UB | Estimate | Std.Error | 95%CI\_LB | 95%CI\_UB |
| **H1: Traditional Media → Customer Value** | 0.19\*\* | 0.11 | 0.01 | 0.41 | -0.40\*\* | 0.13 | -0.76 | -0.15 |
| **H2: Social Media → Customer Value** | -0.22\*\* | 0.10 | -0.42 | -0.05 | 0.28 [ns] | 0.14 | -0.01 | 0.61 |
| **H3: Place → Customer Value** | 0.34\*\* | 0.07 | 0.20 | 0.48 | 0.53\*\* | 0.08 | 0.36 | 0.69 |
| **H4: Price Promotion → Customer Value** | -0.05[ns] | 0.07 | -0.17 | 0.09 | -0.12\*\* | 0.07 | -0.29 | -0.03 |

NB. This table shows the estimates of path coefficients and their boot strap standard errors (SE) and 95% confidence intervals. \*\* Indicates the estimate is statistically significant at alpha = .05. OS= operation system.

**Table 4. Reliability and Validity of Measures**

|  |  |  |  |
| --- | --- | --- | --- |
|   | Cronbach's alpha | Dillon-Goldstein’s rho | Average Variance Extracted (AVE) |
|  Latent Variables | Group 1 | Group 2 | Group 1 | Group 2 | Group 1 | Group 2 |
| 1. Traditional Media | 0.51 | 0.57 | 0.71 | 0.74 | 0.36 | 0.42 |
| 2. Social Media | 0.75 | 0.78 | 0.86 | 0.87 | 0.67 | 0.70 |
| 3. Customer Value | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| 4. Place | 0.39 | 0.45 | 0.52 | 0.55 | 0.34 | 0.38 |
| 5. Pricing | 0.84 | 0.77 | 0.88 | 0.83 | 0.49 | 0.42 |

**NB.:** The R-squared values of endogenous latent variable for customer value are 0.1533 (Group 1-iPhone users) and 0.3641 (Group 2-Android users)

**Table 5. Eigenvalues report**

|  |
| --- |
| **Number of eigenvalues greater than one per block of indicators:** |
| Constructs  | Group 1 | Group 2 |
| 1.Traditional Media | 2 | 2 |
| 2.Social Media | 1 | 1 |
| 3.Customer Value | 0 | 0 |
| 4.Place | 2 | 2 |
| 5.Pricing | 2 | 2 |

**Table 6. Correlations of Latent Variables (SE)**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| 　 | 1 | 2 | 3 | 4 | 5 |
| 1. Traditional Media | **1** | 0.79 | -0.16 | 0.15 | 0.47 |
| 2. Social Media | 0.72 | **1** | 0.04 | 0.24 | 0.46 |
| 3. Customer Value | 0.14 | -0.02 | **1** | 0.52 | -0.1 |
| 4. Place | 0.33 | 0.19 | 0.36 | **1** | 0.14 |
| 5. Price Promotion | 0.27 | 0.28 | -0.01 | 0.15 | **1** |

Group 1 [iOs] blew the diagonal. Group 2 (Android) above the diagonal.

**Fig 2. Empirical Model**

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Source: authors’ own

**Study 2- Ad hoc**

*Design and sample*

The objective of *Study 2* is to offer further support to *Study 1*, where we examined high and low value customers’ engagement with media (both traditional and social media) across handset operation systems. Study 1 used customer self-reported purchase frequency, product ordering and spending. We now expand customer value to more objective metrics using direct product sales.

The data were reused from another prior study conducted in 2017 by a different group of senior executive consultants who registered on a reputable British business school. The students again, used China as the context of their research. The project including the data acquisition were fully consented by ethical committee of the institution concerned. The data was from a different national leading brand of FMCG consumer products offered to the Chinese market with approximately 20% of the market share for the product category. This branded product also has a product line with high value product (aiming at more affluent consumers) and low value product (aiming at perhaps more price sensitive but still brand conscious consumer). To promote the sales of the product in Chinese market, the company launched extensive social media campaign using WeChat in China.

Our dataset acquired the following: (1) product sales data for 16 months between 13/04/2015-31/07/2016; there were a number of different channels this brand utilized: i.e. specialized stores and supermarket; and e-commerce websites; the overall aggregated sales across 16 months was around 10 billion RMB. (2) social media data operationalized by WeChat messages pushed to consumers- which totaled amounted to 310 messages; this data was tracked by a third-party agency; the consumer participation count was 1.3 million and unique visitors to these WeChat push messages were nearly 0.9 million. Sharing of such social media was 0.5 million and unique sharer (i.e. excluding consumer who shared more than once) was 0.3 million. (3) We also had customer terminal operation system data, where 0.1 million consumers used PC Weibo to interact with FMCG product; whilst 0.3 million consumers used mobile phones (we did not have further information which specific OS for their mobile devices due to data limitation). (4) We manually matched daily sales performance data with social media data by date, where the patterns for social media campaigns was less regular. In other words, there were not a clear pattern to be captured by social media campaigns-sometimes a next campaign was followed in a week, sometimes they were launched in a row e.g. from 2015-05-19 to 2015-05-22 there were daily launch of new wave of social media campaigns and we matched the four different social media engagement data by count i.e. total participation, total shares (of the WeChat push), unique participant, and unique sharer.

The daily sales data was further categorized into (2x2) different types per their sales channel and per their product value i.e. high vs. low. Specifically, high value product sold in e-commerce; and high value product sold in traditional channel; and low value product sold in e-commerce, and low value product sold in traditional channel. Negative numbers typically refer to loss or refund. The descriptive analyses were in table below.

**Table 7. Descriptive analysis for channel sales and social media data**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | High Value E-com | High Value Traditional | Low Value E-com | Low ValueTraditional | Total Participation | Unique Participant | Total Shares | Unique Sharer |
| Mean | 3621.10 | 3240.35 | 4585.91 | 4039.15 | 12024.79 | 7859.94 | 5039.50 | 2887.09 |
| S.D. | 1792.19 | 7278.07 | 2267.88 | 9366.36 | 17753.91 | 11526.47 | 6534.32 | 4079.99 |
| Min | -907.05 | -1112.27 | -6592.58 | -2082.37 | 2.00 | 2.00 | 2.00 | 2.00 |
| Max | 42150.54 | 21809.15 | 37238.40 | 27077.51 | 51136.00 | 35764.00 | 26323.00 | 14139.00 |

NB: e-commerce sales data reported in “in-MKT”= factory to the distributor; sales data for traditional channel reported in “off-take”= distributor to the retail outlets. S.D.= standard deviation;

SmartPLS4 (Ringle, et al., 2022) was deployed to build a structural model to understand how consumer’s engagement with social media influence product sales as measured by channel (e-commerce vs. traditional) and product value (high vs. low). We used formative indicators of the four social media engagement (total participation, total shares, unique participant, and unique sharer) to form the latent variable social media engagement. For time periods where sales were generated but there were no recorded and matching social media campaigns, we treat these missing values in smartPLS4 using mean replacement. And we then performed bootstrapping in the same software to generate t-values for each hypothesized path relationship.

Results show that: Social Media Engagement → HighValue x eCommerce channel ꞵ=0.25 [n.s], Social Media Engagement → HighValue\*Traditional channel ꞵ =-0.68\*\*\*; Social Media Engagement → LowValue\* eCommerce channel ꞵ=0.25 [n.s.], and lastly, Social Media Engagement → LowValue\* Traditional channel ꞵ=0.03 [n.s.]. Therefore, in this dataset, we find support for social media engagement negatively associated with sales for high value FMCG product concerned in the traditional channel. Of course, due to aggregated data, we cannot obtain customer value data, but the products’ actual sales data as DV in this modelling.

**Fig 3. PLS Empirical Model**

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NB: “in-MKT”= factory to the distributor; “off-take”= distributor to the retail outlets. 5000 subsamples bootstrapping, confidence interval method: studentized bootstrap; two tailed, significance level 0.05.

**Table 8. PLS result for hypothesized relationships**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (|O/STDEV|) | P values |
| Social Media Engagement -> HighValue\*eCommerce channel  | 0.25 | 0.19 | 0.22 | 1.16 | 0.25 |
| Social Media Engagement -> HighValue\*Traditional channel  | -0.68\*\* | -0.56 | 0.31 | 2.18 | 0.03 |
| Social Media Engagement -> LowValue\* eCommerce channel | 0.25 | 0.24 | 0.49 | 0.50 | 0.62 |
| Social Media Engagement -> LowValue\* Traditional channel | 0.03 | -0.03 | 0.31 | 0.09 | 0.93 |

**Conclusions**

Results show that OS does moderate the impact of customer traditional media engagement on their customer value, where iOS positively moderates this relationship but their Android counterparts negatively moderated this relationship. Further, for the effect of social media engagement on customer value, we find OS partially moderates this relationship with more profound impact from iOS (with negative impact). Our sales dataset in study 2 further lends support that social media engagement negatively associated with high value FMCG product sales sold in the traditional channel. From the marketing mix management perspective where both iOS and Android users have a positive significant impact on this place on customer value, we argue that Android group has stronger positive moderation impact that iOS. Lastly, for the hypothesized moderation effect on price promotion on customer value, we find the Android group strongly and negatively moderate this relationship.

Our findings contribute some important implications for retailers and mobile advertisers. Results shown online consumers who use iPhone and those who use Android can exhibit different media engagement and even their responses to marketing stimuli vary. These would all contribute to divergent customer values. Advertisers need to avoid spending excessively in traditional media vehicles if their target audience falls into the Android users. iPhone users in contrast, are more sensitive to traditional media engagement. To promote on iOS, marketers need to engage more on traditional media in order to maximize their promotional efforts as we found counter-intuitively, the use of iOS weakens the impact of social media engagement on customer value.

The marking mix managers would also gain insights from this study where conventional wisdom inform that Android users are less rich compared with iOS, this does not mean more aggressive price promotion can convert buying behavior and contribute to higher customer value for Android shoppers. For multi-channel retail managers, place remain an important driving factor to customer value, whilst such relationship holds true for both iOS and Android shoppers, place experiences affect strongly for both type of online shoppers on different OS, however, android users seem to have a stronger positive effect of this.

To the best of our knowledge little prior empirical academic work has been done on examining differences between Android and iOS users from the customer value perspectives with both marketing mix perspective and media engagement perspective combined. Understanding of which would contribute to mix management, segmentation, and social media engagement marketers. Findings from this study contributes to retailing literature in a few areas: (1) it provides further evidences to support the process view of consumers retail buying (Johansson, 2001). We find neither traditional media nor social media is to replace each other, but forming a web where customer navigate for their benefit. (2) it contributes to our understanding that customers are actively involving in value creation process in retail buying through various media engagement, access of products from different place of purchase and as a joint result of price promotion messages. (3) We find social media experiences for retail buying are important, but iOS users may have some unique needs and wants that are met in traditional media engagement. Value creation is not only limited to social media.

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1. Customer spending is measured in 5 tiers, with 1 represents less than 100 RMB, 2=100-199 RMB; 3=200-299 RMB; 4=300-399 RMB, and 5= larger than 399. Purchase frequency is measured 1 equals ‘highly frequent’ i.e. larger than 4 times per month; 2= frequent (>3); 3=’average (>2)’, and 4= ‘below average, (>1); and 5 = inactive (<1); age groups are: 1=”<25”; 2=”25-30”; 3=”31-35”; 4=”36-40”; 5=”41-45”; 6=”46-50”; 7=”>50”. Gender: 1= female, 2= male; Level of education: 1= middle school; 2= high school; 3=undergraduate; 4= postgraduate and above; Tier of cities participants are from: 1= Tier 1 cities; 2= tier 2 cities; 3= other (lower) tier cities; Monthly salary range: 1=”<2,000RMB”; 2=”2,001-3,000RMB”; 3=”3,001-5,000RMB”, 4=”5,001-8,000RMB”, 5=”8,001-12,000RMB”, 6=”12,001-20,000RMB”, 7=”20,001-30,000RMB”, 8=”30,001-40,000RMB”, and 9=”>40,000RMB”. Handset operation system: 1=iPhone; 2=Android system phones; 3= other; Customer value= ordered \* purchase frequency. [↑](#footnote-ref-1)