The Effect of Social Media Apps on Shopping Apps

ABSTRACT

Mobile shopping is on the rise, and the main channel of social media has now shifted from online to mobile. We aim to understand the role of social media apps in driving mobile shopping. Specifically, we examine two performance metrics for mobile shopping—shopping app stickiness and usage time—and classify social media apps into broadcasting and narrowcasting ones. Our empirical analyses using mobile panel data reveal that the usage time of both types of social media apps increases shopping app stickiness. As for shopping app usage time, broadcasting app usage time has a positive impact, while narrowcasting app usage time has a negative impact. We also find that the impact of broadcasting app usage is greater than that of narrowcasting app usage. Furthermore, offline social interactions weaken the effect of social media usage on shopping app stickiness and that of broadcasting app usage on shopping app usage time.

Keywords: mobile shopping, mobile application, social media, app stickiness, app usage time, offline social interaction

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1. Introduction

Mobile applications (hereafter, apps) have reshaped the way companies interact with consumers and created business opportunities. Above all, shopping apps have become central to growing retail businesses (Statista, 2020) as the majority of mobile users purchase products and look for stores or product information using shopping apps (App Annie, 2020). Indeed, shopping app downloads grew around 17% globally within a year between 2019 and 2020 to over 6.2 billion (Apptopia, 2021). Social media apps are undoubtedly another category of key importance. Consumers are now accustomed to using social media as the main source to look for product reviews and brand recommendations before purchase (Forbes, 2019), especially for Gen Z and Millennials (Alalwan et al., 2017). As such, companies endeavor to make good use of social media, communicating brand information and eventually inducing consumers to turn into buyers.

Prior studies have shown that social media influences consumers' shopping behavior. For example, communications about products over social media affect purchase intention (Grewal et al., 2019; Wang et al., 2012). Social media usage (Zhang et al., 2017) and product recommendations in social media (Gupta & Harris, 2010) also influence online shopping intention and activities. As mobile shopping is on the rise and the main channel of social media has now shifted from online to mobile, the effect of social media usage on shopping should be revisited in the mobile context. Despite the growing popularity of mobile shopping and the prevalent use of social media apps, there is little research that examines the relationship between these two app categories. Therefore, our research investigates the effect of social media apps on shopping apps.

We examine the role of social media in driving customers' usage of shopping apps. Unlike conventional financial metrics centered on sales, we focus on two customer-based marketing metrics—usage time spent on an app (i.e., app usage time) and the frequency of app visits (i.e., app stickiness)—that are widely employed in practice as key performance metrics in the mobile app context (Braze, 2016; McKinsey & Company, 2019). Furthermore, as social media has diversified, not all social media have the same effects on shopping app usage. As such, social media apps are classified into those for broadcasting vs. narrowcasting. Therefore, our research addresses the following important research questions about the impact of two types of social media apps (i.e., broadcasting vs. narrowcasting) on two metrics of shopping app usage (i.e., app stickiness and usage time):

(1) How do usage times of broadcasting social media app (hereafter, broadcasting app) and that of narrowcasting social media app (hereafter, narrowcasting app) differently affect shopping app stickiness?
(2) How do usage times of broadcasting and narrowcasting app differently affect shopping app usage time?
(3) How do offline social interactions moderate the effects of social media app usage?

To address these questions, we obtain proprietary mobile panel data, including mobile log, panel survey, and real-time location information from a global marketing research company, and run two truncated regressions of shopping app stickiness and usage time. Our empirical results provide important findings. First, we find that social media app usage increases shopping app stickiness regardless of the type of social media apps. However, broadcasting app usage increases shopping app usage time, whereas narrowcasting app usage decreases it. Thus, time spent on shopping apps changes, depending on the kinds of social media apps consumers use prior to shopping app usage. Furthermore, the impact of broadcasting app usage is greater than that of narrowcasting app usage in increasing both shopping app stickiness and usage time. Finally, offline social interactions weaken the effects of social media app usage on both app stickiness and usage time.

This research makes several theoretical and practical contributions. First, this research contributes to the limited body of mobile app literature by understanding the relationship between two app categories—social media and shopping—that are popular and managerially important. By investigating the effects of broadcasting and narrowcasting apps separately, we provide managers with useful guidelines on marketing budget allocation across social media apps. Second, this research answers recent calls for more research on performance metrics for mobile apps. Past studies on shopping apps and websites have focused on purchase as an outcome, and app browsing behavior has received relatively limited attention in the literature. Especially, we examine *app stickiness* which is a mobile app performance metric popular in practice but understudied in academia, along with the more studied app usage time. Our results on two distinct app performance metrics provide managerial insights into the evaluation of customer engagement in shopping apps, equipping managers to improve their mobile marketing strategies. Third, our findings such as that offline social interactions moderate the impact of social media app usage on mobile shopping can provide managers strategic guidelines for how to utilize location information in social media marketing for a successful mobile shopping business. For example, geo-targeting social media ads or location-based coupons via social media may outperform in regions with relatively little in-person social interactions.

We organize the rest of the paper as follows. First, we discuss the related literature and develop hypotheses. We then describe data and variables and present our modeling framework.

Next, we report estimation results and explain empirical findings. Finally, we discuss implications and directions for future research.

2. Related Literature

2.1 Performance Metrics for Shopping Apps

Shopping apps not only provide a marketplace for mobile transactions but also work as a brand communication channel, allowing for seamless connection with customers and increasing customer engagement (Wang et al., 2015). To successfully manage shopping apps in the long run, it is necessary to track performance metrics including not only financial metrics such as sales but also marketing metrics. Marketing metrics, indicating the degree to which customers are engaged with an app, reveal some underlying characteristics of customers and their attitudes/intentions toward a company and are known to be correlated with financial performance (Best, 2013). Among marketing metrics, usage time spent on an app (i.e., app usage time) and the frequency of app visits (i.e., app stickiness) are widely employed in practice as key marketing metrics to analyze app browsing behavior and evaluate consumer engagement in the mobile app context (Braze, 2016; McKinsey & Company, 2019). Given that browsing and purchasing are highly correlated in the online shopping context (Moe, 2003; Schlosser et al., 2006), the two key performance metrics of app browsing behavior (i.e., app usage time and app stickiness) have been critical factors in practice to predict sales performance as well as customer engagement in a shopping app.

The importance of usage time in understanding app or website performance has been documented in academia as well. For example, a longer usage time per website visit captures interest in the items featured and eventual purchasing (Holsing & Olbrich, 2012). Similarly in the mobile app context, as usage time in a mobile game app increases, purchase intention for in-app services tends to increase (Hsiao & Chen, 2016). Furthermore, the browsing time of shopping apps is associated with not only purchase likelihood but also variety seeking in shopping app choice (Kim et al., 2017). On the other hand, the second marketing metric of our interest, app stickiness, has been relatively under-studied as compared with app usage time. App stickiness is a metric of users' visit frequency of an app and reflects users' behavioral intention to continuously re-use the app. Stickiness in an online setting has been recognized as a critical metric of a deep-rooted commitment to websites (Li et al., 2006), loyalty to e-commerce sites (Gommans et al., 2001), and engagement for further interactions on websites (Chen & Sockel, 2004). However, these studies have examined stickiness for websites (called website stickiness or site stickiness), and there is a lack of literature investigating stickiness in a mobile setting (i.e., app stickiness). Furthermore, to the best of our knowledge, there is no research that jointly investigates the two critical marketing metrics of app browsing behavior in a single framework and analyzes differences in marketing effects between them. In this study, we fill this gap in the literature by focusing on both usage time and app stickiness to better understand shopping app browsing behavior.

2.2 Social Media and Shopping

Social media is a digital community in which participants socially and virtually interact with each other creating and consuming content of one's ideas, interests, information, etc. As consumers congregate online, brands also participate in social media by generating and distributing content about themselves. That is, social media can help brands establish trust in brand-related content and build loyalty (Nisar & Whitehead, 2016), hoping to increase brand sales online (Kumar et al., 2013). Unsurprisingly, the effect of social media on consumers' online purchases has been actively investigated. Consumers with a favorable attitude towards social media influencers would have an intention to purchase influencers' supported products (Lim et al., 2017). Social ties cultivated from online interactions on social media also influence consumers' purchase behavior (Yang & Che, 2020). A high level of perceived interactivity with advertising on social media makes such advertising more entertaining, leading to the online purchase of products or services featured (Alalwan, 2018).

As mobile shopping is on the rise, the interest in the effect of social media usage is expanded into mobile shopping. For example, the need for social connection through social media not only facilitates online shopping but also affects the intention to shop mobile (Kumar et al., 2015). The increased use of social media helps consumers form favorable attitudes toward mobile shopping (Dwivedi et al., 2021; Hossain et al., 2020). Moreover, mobile shopping is continuously preferred by those who rely on mobile social circles and value social interactions on social media (Lu et al., 2017). Despite the growing body of literature on the relationship between social media and mobile shopping, little attention is paid to the context of using mobile apps. Thus, we aim to offer insights into how social media app usage influences shopping app usage.

2.3 Broadcasting vs. Narrowcasting Social Media

Given the overwhelming importance and diversity of social media apps in our daily lives, it is worthwhile to classify social media as broadcasting or narrowcasting by comparing and contrasting them in different aspects. Social media apps for broadcasting are suitable when communicating with large and diverse audiences, such as in the cases of Facebook and Twitter

(Cappella, 2017). In contrast, social media apps for narrowcasting work better when conversing with a small group of well-acquainted or selected others, such as in the cases of WhatsApp and WeChat (Foti et al., 2020).

Broadcasting social media allows communicators to efficiently reach many and broad audiences (Scholz et al., 2020). When targeting broad audiences, the sharers in social media tend to focus on self and share self-related messages (Barasch & Berger, 2014). In addition, because they do not know the audience intimately and feel psychologically distant (Dubois et al., 2016), they avoid messages that make them look bad and are more likely to communicate positive information (Barasch & Berger, 2014; Ju et al., 2017). On the other hand, narrowcasting through social media relies on psychological intimacy and involves exchanging somewhat private information (Scholz et al., 2020). As narrowcasted messages are directed at specific individuals or groups (Bazarova & Choi, 2014), they tend to focus more on the recipient and what the listener might find helpful than the broadcasted ones (Barasch & Berger, 2014). In addition, narrowcasted messages are often self-disclosing, honest, and occasionally negative, intended to close psychological distance and build emotional bonds (Chen, 2017; Dubois et al., 2016).

Broadcasting and narrowcasting apps may also differ in the size of influence they have on the audience. From the audience's perspective, communicators of broadcasting apps are those who can be characterized as weak ties (Peng et al., 2018; Granovetter, 1973) or distant others (Zhao & Xie, 2011). In social network studies, the strength of weak ties is well recognized as the source of diverse information that the strong ties may lack (Granovetter, 1973). That is, the audience looking for diverse shopping information can find information from broadcasting apps more useful than that from narrowcasting apps. In addition, because product discussion tends to be impersonal, it fits impersonal media such as broadcasting apps well (Brasch & Berger, 2014;

Scholz et al., 2020). Thus, although people get shopping-related information from both types of social media apps, information in broadcasting apps may be considered more diverse and objective than that in narrowcasting apps. This substantial disparity between broadcasting and narrowcasting apps calls for studies comparing and contrasting their distinctive effects on mobile shopping.

2.4 Offline Social Interactions and Shopping

Offline social interaction is "face-to-face" interaction with people, including all the non-technology-mediated interactions in person (Lieberman & Schroeder, 2020). Similar to online social interaction, it provides social learning through information sharing and observation (Choi et al., 2010; Iyengar et al., 2015; Zhang et al., 2015). Indeed, the role of offline social interactions in driving online shopping is well established (Chen et al., 2011; Katona et al., 2011; Zhang et al., 2015). A large number of literature proxies for offline social interactions using, for instance, the installed customer base (Choi et al., 2010) and interaction likelihood among target customers (Choi et al., 2012). Other studies utilize data on region-level social capital in support of significant social influence (Lee & Bell, 2013; Kim et al., 2019). Only few studies directly measure offline social interactions at the individual level and find consistent support for its effect on technology adoption (Tucker, 2008) and repeat usage (Iyengar et al., 2015; Toker-Yildiz et al., 2017).

When offline social interactions are compared with the online counterpart, face-to-face interactions occurring offline contain subtle but qualitative information from paralinguistic cues such as facial expressions, voice, and body language (Knop et al., 2016; Reich et al., 2012) and thus exerts a stronger influence. Moreover, people are likely to disclose themselves to a greater extent during offline social interactions, hoping for closer relations and tighter emotional bonding (Chan & Cheng, 2004). This means that the affluence of information obtained from offline social interactions could outweigh online information, possibly resulting in reducing the influence of online social interactions.

As mentioned earlier, the widespread use of mobile devices for shopping warrants the understanding of the relationship between offline social interactions and mobile shopping. Following this stream of prior studies, we examine to what extent offline social interactions exert influence on mobile social interactions. In other words, we study the moderating role of offline social interactions in understanding the effects of social app usage on shopping app usage.

3. Hypotheses

In our study, we examine how social media apps affect each type of shopping app usage behavior—app stickiness (i.e., frequency of app visits) and app usage time (i.e., usage time spent on an app). Since not all social media have the same effects on shopping app usage, we propose the hypotheses about the impact of each type of social media app (i.e., broadcasting vs. narrowcasting) on two metrics of shopping app usage (i.e., app stickiness and usage time), respectively.

[Insert Figure 1 about here]

3.1 The Impact of Social Media Apps on Shopping App Stickiness

Social media apps act as a popular medium to acquire product information (Jain et al., 2018). Consumers use social media to post product reviews and share promotional events, and branded accounts on social media help companies communicate brand stories and product information with consumers (Villarroel Ordenes et al., 2019; Sokolova & Kefi, 2020). Such user-or brand-generated content is likely to make consumers more engaged with shopping (Goh et al., 2013; Lee et al., 2018; Malthouse et al., 2016) and trigger consumers to visit offline stores or online shopping websites (Dolega et al., 2021; Kumar et al., 2016). As such, consumers exposed to product-related social media content for a longer period of time will experience a heightened interest in shopping, leading to an increased likelihood to visit stores (Zhang et al., 2017).

Furthermore, consumers ask for product referrals through social media and evaluate alternatives using the information in social media (Dolega et al., 2021). They often purchase products recommended by influencers in social media and visit brands' websites after observing that people they know liked their sponsored content (Mattke et al., 2020). This kind of herd behavior in shopping due to the information in social media simplifies decision heuristics when consumers encounter product/retailer information overload (Simpson et al., 2008), which may drive people to use social media apps before visiting shopping apps.

Consumers are exposed to shopping- or product-related content from distant others such as anonymous reviewers or branded communicators through broadcasting apps as well as from close others like friends and family through narrowcasting apps (Hajili, 2014; Zhang et al., 2017). Therefore, app stickiness (i.e., the frequency of app visits) will be positively impacted by more time spent on social media, regardless of whether it is narrowcasting or broadcasting apps. Thus, we hypothesize that the greater usage time on either broadcasting or narrowcasting apps will increase the likelihood of being exposed to product-related content, thus stimulating shopping needs and inducing consumers to visit shopping apps. We posit the following:

H1a: The usage time of broadcasting apps is positively associated with shopping app stickiness.

H1b: The usage time of narrowcasting apps is positively associated with shopping app stickiness.

While the impact of social media apps on shopping app stickiness is positive regardless of whether they are broadcasting or narrowcasting ones, the size of the influence may differ. Broadcasting apps provide varied content and up-to-date product news generated by numerous content creators (including branded accounts) (Cappella, 2017; Hutter et al., 2013). Consistent exposure to such stimulation will encourage consumers to visit the store (i.e., activate the app in the mobile context) more frequently. Furthermore, as noted earlier, broadcasting apps can have a greater impact on shopping intention when message diversity is important (Granovetter, 1973). Hence, exposure to diverse recommendations in broadcasting apps over a period of time will likely induce consumers to visit various shopping apps more frequently and thus increase app stickiness.

In addition, despite product recommendations from strong ties tends to be more relevant and specific, those from weak ties through broadcasting apps can be more informative and persuasive at the initial shopping stage when consumers focus on abstract and general product/retailer information to narrow down possible shopping options (Song, Yi, & Huang, 2017). Thus, we conjecture that the broadcasting apps have a greater impact on shopping app stickiness than the narrowcasting ones.

H1c: The impact of broadcasting app usage time on shopping app stickiness is greater than that of narrowcasting app usage time.

3.2 The Impact of Social Media Apps on Shopping App Usage Time

While app stickiness directly concerns consumers’ interest in a particular retailer, app usage time is more related to interest in items featured in a store (Li et al., 2006; Moe, 2003). That is, spending a longer time on shopping apps indicates more browsing in the apps and gives users more time to complete purchase transactions (Holsing & Olbrich, 2012). The disparity in audience size and network members between two types of social media apps will shape the messages shared through them and result in distinct outcomes on shopping app usage time.

Prior studies have underlined that communicating to distant audiences prompts users to share positive over negative information, whereas talking to close audiences drives users to share negative over positive information (Barash & Berger, 2014; Dubois et al., 2016; Ju et al., 2017). This suggests that users of broadcasting apps are more likely to generate and consume positive content, while those of narrowcasting apps will be exposed to negative content to a greater extent. Furthermore, communicators of broadcasting apps tend to post and share self-oriented (i.e., brand-focused) content because they face a diverse and lesser-known audience, while narrowcasting ones feature other-oriented (i.e., audience-focused) content tailored to message recipients (Ju et al., 2017). Thus, broadcasting social media users get more diverse but less relevant information, while narrowcasting social media users get more relevant but limited information (Balaji et al., 2016; Chen, 2017). Taking all together, users of broadcasting apps will be exposed to broad topics and positive content, whereas those of narrowcasting apps are likely to see tailored albeit negative information. Therefore, a longer usage time on broadcasting apps leads to an increased interest in browsing various products, making consumers spend longer time on the apps. However, consumers who spend longer time on narrowcasting apps are more likely to receive relevant and credible product information from close others, which may help them to narrow down product consideration sets in a shopping process and increase purchase intention (Koo, 2016). This will result in more efficient shopping experiences and less usage time on shopping apps. Thus, we hypothesize that:

H2a: The usage time of broadcasting apps is positively associated with shopping app usage time.

H2b: The usage time of narrowcasting apps is negatively associated with shopping app usage time.

Broadcasting apps will have a greater impact on shopping app usage time than narrowcasting ones for similar reasons as in the case of shopping app stickiness. That is, diverse and abundant recommendations coming from weak ties and distant others will have a bigger influence on time invested in browsing and purchasing process (Granovetter, 1973), while limited and focused recommendations from strong ties (i.e., close others) will be more relevant but less in number for a given period and thus have less impact on shopping app usage time. Thus, we hypothesize that:

H2c: The impact of broadcasting app usage time on shopping app usage time is greater than that of narrowcasting app usage time.

3.3 The Moderating Role of Offline Social Interactions

Consumers in the offline environment discuss a broad scale of topics and disclose more straightforward and intimate information by sharing private information, experience, thoughts, and emotions in real time (Chan & Cheng, 2004; Knop et al., 2016). Offline social interactions help consumers not only better communicate information but also benefit from nonverbal and paralinguistic cues containing rich emotion (Chawla & Krauss, 1994). These offline social interactions occur even in the absence of direct communication (Banerjee, 1992). Indeed, observation-based influence plays a key role in understanding the role of social interactions in driving both offline and online shopping (Choi et al., 2010; Kim et al., 2019). For instance, by observing people offline, consumers understand and judge the quality of new products or have interests in them (Zhang et al., 2015). Situational and non-verbal communication cues (e.g., tone of voice and facial expressions) obtained through offline social interactions are additional sources of personal information, which moderates the impact of online information and changes an individual's online behavior (Nguyen et al., 2012). Thus, when consumers can obtain product- and shopping-related information through either direct interactions or indirect observation occurring offline, they are entitled to rely less on digital content for shopping. Hence, the effect of social media on mobile shopping will decrease if consumers have alternative sources of product information through offline social interaction. Thus, we hypothesize that:

H3: Offline social interactions weaken the effect of usage time of (a) broadcasting apps and (b) narrowcasting apps on shopping app stickiness. Offline social interactions weaken the effect of usage time of (c) broadcasting apps and (d) narrowcasting apps on shopping app usage time.

4. Data

We obtained proprietary mobile panel data of mobile log and panel survey from a global market research company. The company collected the mobile log of 538 smartphone users by tracking their mobile browsing behaviors through a tracking app for five months between July and November 2012. The log data consists of individual-level logs of browsing histories, including the names of apps used, times of apps opened and closed, and GPS coordinates. We focus on 43 shopping apps, including brick-and-mortar and e-commerce retailers, and 24 social media apps providing broadcasting and narrowcasting social networking services.[1]

[1] 43 shopping apps included in our analysis represent over 93% of total shopping app usage by session count in our data. 24 social media apps represent approximately 97% of total social media usage by session count. We exclude

To take into account any locational effect on mobile usage, we supplement the log data with region-specific information. We figure out regions in which users were at that time based on the coordinates of users' real-time locations available in the mobile log data. Then, we merge relevant region information with the mobile log data. We include the floating population and the number of transportation users by region in 2010[2], and the number of nearby offline stores at that time in 2012, including restaurants and bars obtained from the Korean Statistics Information System (KOSIS). The number of cafes in a region is collected from Small Enterprise and Market Service System (SEMAS) and combined with the number of restaurants and bars in which offline social interactions mainly take place. We also control for daily weather information in each region using temperature and precipitation in 2012 retrieved from Korea Meteorological Administration (KMA).

In addition, the panel survey conducted in August 2012 consists of questions about online and mobile experience and socio-demographics that cannot be collected via a tracking app. The panel survey data mainly contains user characteristics and mobile usage information that are expected to affect consumer shopping behavior in general, such as age, gender, and income level.

5. Measures and Model

5.1 Measures

Dependent variables. We measure mobile shopping behavior using two variables, *shopping app stickiness* and *shopping app usage time*. The *shopping app stickiness* of user *i* with app *j* at session *t*, $ShoppingAS_{ijt}$, is the ratio of app *j* accessed by user *i* within 30 days prior to a

minor apps which account for less than 0.01% of either social media app usage or shopping app usage.

[2] Since KOSIS reports the floating population and the number of transportation users by region every 5 years, we use the information of year 2010 which was the closest to the main data period of our study (i.e., 2012).

day in which session t begins. It is calculated as the number of days that user i accesses shopping app j in the last 30 days divided by 30. The *shopping app usage time* or $ShoppingUT_{ijt}$ is the daily usage time of shopping app j by user i in a day in which session t occurs. As shown in Table 1, the average shopping app stickiness is 0.244, indicating that on average, a user activates a shopping app for 7.32 days over the window of 30 days. Also, a user spends 0.221 hours (i.e., 13.26 minutes) on average per session.

Main effect variables. We classify 24 social media apps into 15 broadcasting ones (i.e., social media apps on which the receivers of content or messages are large or unclear) and nine narrowcasting ones (i.e., social media apps on which the receivers of content or messages are small and clear). Using each app of both types, we compute *broadcasting app usage time* and *narrowcasting app usage time*, $BroadcastUT_{ijt}$ and $NarrowcastUT_{ijt}$, as the average usage time of app j by user i within 24 hours prior to session t, respectively. The average usage time of narrowcasting apps within a day prior to shopping app usage is 0.528 hours per session, while that of broadcasting apps is 0.144 hours per session, suggesting that a user spends much longer time on narrowcasting apps than broadcasting counterparts.

Interaction effect variable. Offline social interactions are likely to occur in multi-purpose community facilities such as restaurants, cafes, and bars. Indeed, the most frequently checked-in places in social media are directly related to dining, food, and nightlife (Kylasa et al., 2016; Ye et al., 2011). Also, social networking buzz through offline social interactions mainly occurs in cafes, restaurants, and bars (Pratt, 2008). These socially vibrant places are where private conversation such as shopping information and favorite brands mainly takes place. People feel comfortable and trusting during social eating and therefore engage in more social activities (Dunbar, 2017). This suggests that a higher density of these facilities in a region is associated with a greater likelihood of offline social interactions. That is, if someone visits a region with a high density of those facilities, she or he is likely to experience offline social interactions. Furthermore, visiting multiple regions with many social activities will provoke more observational learning. Past studies show that observing others offline can affect consumers' online shopping trials (Lee & Bell, 2013) and purchases (Choi et al., 2010). Hence, we operationalize *offline social interactions* that user *i* may have been exposed to and experienced within a day before using shopping app *j* at session *t*, $OfflineSI_{ijt}$, as the aggregated density of restaurants, cafes, and bars in all the regions that user *i* visited within a day prior to session *t*. $OfflineSI_{ijt}$ is log-transformed to adjust for its right-skewness.

Control variables. We include control variables that may be associated with users' mobile shopping behavior in order to measure the real effect of social media app usage and also the variables reflecting regional environment to focus on the effect of socially vibrant places as the key driver of offline social interactions. First, we control for app-specific characteristics by including the dummy variables for omni-channel and premium (selling high-end products) retailers. Second, we include the variable of offline shop exposure operationalized as the total number of offline stores available in the regions visited within a day prior to session *t* in log form. Third, the set of region-level control variables includes floating population, the number of public transportation users, temperature, and precipitation of a region in which shopping app is currently in use. Fourth, we include temporal indicators for evening and weekend, and month dummies using session timestamps. Finally, we control for individual-level heterogeneity by adding daily app usage time, age, gender, and income (median household income level).

Table 1 shows the descriptive statistics of the aforementioned variables. We conduct two regression analyses using shopping app stickiness and shopping app usage time as dependent variables and all the other ones in Table 1 as independent variables. All the VIF values range between 1.02 and 2.11, far smaller than 10 (Hair et al., 2006), confirming that there is no significant evidence of multi-collinearity.

[Insert Table 1 about here]

5.2 Truncated Regression Model

We examine the effect of social media app usage on both *shopping app stickiness* and *shopping app usage time*. Both dependent variables are always positive since the session log is recorded only when the shopping app is activated. Therefore, we employ truncated regression models. The main effect model is:

$$(1)\quad ShoppingAS_{ijt} = \beta_{1,1}BroadcastUT_{ijt} + \beta_{1,2}NarrowcastUT_{ijt} + \theta_1 Controls_{1,ijt} + \varepsilon_{1,ijt}$$

$$(2)\quad ShoppingUT_{ijt} = \beta_{2,1}BroadcastUT_{ijt} + \beta_{2,2}NarrowcastUT_{ijt} + \theta_2 Controls_{2,ijt} + \varepsilon_{2,ijt}$$

where the effects of broadcasting and narrowcasting app usage time on shopping app stickiness are captured by $\beta_{1,1}$ and $\beta_{1,2}$, respectively. Likewise, $\beta_{2,1}$ and $\beta_{2,2}$ measure the effects of broadcasting and narrowcasting app usage time on shopping app usage time, respectively. θ_1 and θ_2 are the parameter vectors for all the control variables, including individual and app characteristics, regional information, and time dummies.

We then move to the interaction model to further examine the moderating roles of offline social interactions in this context. The interaction effect model is:

$$(3)\quad ShoppingAS_{ijt} = \beta_{3,1}\, BroadcastUT_{ijt} + \beta_{3,2}\, NarrowcastUT_{ijt}$$

$$+ \beta_{3,3}\, BroadcastUT_{ijt} \cdot OfflineSI_{ijt} + \beta_{3,4} NarrowcastUT_{ijt} \cdot OfflineSI_{ijt}$$

$$+ \beta_{3,5} OfflineSI_{ijt} + \theta_3 Controls_{ijt} + \varepsilon_{3,ijt}$$

$$(4) \quad ShoppingUT_{ijt} = \beta_{4,1}\, BroadcastUT_{ijt} + \beta_{4,2}\, NarrowcastUT_{ijt}$$

$$+\beta_{4,3}\, BroadcastUT_{ijt} \cdot OfflineSI_{ijt} + \beta_{4,4}\, NarrowcastUT_{ijt} \cdot OfflineSI_{ijt}$$

$$+ \beta_{4,5}\, OfflineSI_{ijt} + \theta_4\, Controls_{ijt} + \varepsilon_{4,ijt}$$

where the main effects of social media app usage time on shopping app stickiness are captured by $\beta_{3,1}$ and $\beta_{3,2}$. Likewise, the effects on shopping app usage time are captured by $\beta_{4,1}$ and $\beta_{4,2}$. The moderating effects of offline social interactions are captured by $\beta_{3,3}$ and $\beta_{3,4}$ for shopping app stickiness, and $\beta_{4,3}$ and $\beta_{4,4}$ for shopping app usage time. Same as in the main effect model, θ_3 and θ_4 are the parameter vectors for the control variables.

6. Empirical Findings

Table 2 presents the estimation results of both the main effect and interaction effect models. The directions and significances of the parameter estimates of both models by and large stay the same statistically and the hypothesis test results remain the same in both models; however, the smaller AIC value of the interaction effect model shows a better fit. Thus, our discussion of empirical findings centers on the interaction effect model.

[Insert Table 2 about here]

6.1 Main Effect Variables

As for shopping app stickiness, we find that both the main effects of broadcasting and narrowcasting app usage times are significant and positive ($\beta_{3,1} = 0.355$, $p < 0.01$; $\beta_{3,2} = 0.029$, $p < 0.01$), supporting H1a and H1b. The positive effects of social media app usage on shopping app stickiness verify the previous findings in the social media literature that the shared information via social media has a positive impact on purchase decision-making (Goh et al., 2013; Xie & Lee, 2015). Furthermore, we find that broadcasting app usage has a larger impact on app stickiness than narrowcasting app usage ($\beta_{3,1} - \beta_{3,2} = 0.326$, $p < 0.01$), supporting H1c. While both broadcasting and narrowcasting apps have a positive impact on app stickiness, broadcasting apps provide more varied content and up-to-date product news generated by numerous content creators than narrowcasting apps (Cappella, 2017; Hutter et al., 2013). As noted earlier, consistent exposure to such stimuli in broadcasting apps will encourage consumers to visit a shopping app more frequently.

Regarding shopping app usage time, broadcasting app usage time is positively associated ($\beta_{4,1} = 0.172$, $p < 0.01$) whereas narrowcasting app usage time has a negative effect on app usage time ($\beta_{4,2} = -0.026$, $p < 0.01$), corroborating H2a and H2b. We confirm that broadcasting app usage has a larger impact on app usage time than narrowcasting app usage ($\beta_{4,1} - \beta_{4,2} = 0.197$, $p < 0.01$), supporting H2c. The difference between the effect of broadcasting apps and that of narrowcasting apps is likely to be attributed to the characteristics of shared information (i.e., emotional valence and relevance) in each app type. As noted earlier, product-related information shared via broadcasting apps, which tend to be more positive and less relevant than those in narrowcasting apps, makes people interested in various products, thereby spending more time on shopping apps for browsing and purchasing after using broadcasting apps (Barasch & Berger, 2014; Granovetter, 1973; Ju et al., 2017). On the other hand, consumers tend to share more detailed and relevant information from reliable people they trust when they use narrowcasting apps (Balaji et al., 2016; Chen, 2017). Therefore, information from narrowcasting apps is likely to contribute to reducing the time to search and evaluate products to purchase in shopping apps.

6.2 Interaction Effect Variables

Our results of the interaction effect models confirm that as offline social interactions increase, the effects of social media app usage time of both kinds on shopping app stickiness weaken ($\beta_{3,3}$ = -0.060, $p < 0.01$; $\beta_{3,4}$ = -0.004, $p < 0.01$), thus supporting H3a and H3b. Also, the effect of broadcasting app usage on shopping app usage time weakens ($\beta_{4,3}$ = -0.020, $p < 0.01$) while that of narrowcasting app usage turns out to be insignificant. Thus, H3c is supported, whereas H3d is not. This finding is likely to stem from richer information acquisition during offline social interactions. Consumers having offline social interactions could obtain product information by observing nonverbal cues of intimate people or actual products in use, potentially favoring information gathered during offline social activity over that found from mobile social media apps.

6.3 Control Variables

Most of the control variables have significant effects on shopping app usage. First, both premium retailers and omni-channel retailers have lower shopping app stickiness and usage time. Unsurprisingly, consumers tend to avoid shopping for high-end products through mobile apps. The negative effect for omni-channel retailers implies that app stickiness and usage time of omni-channel retailers' apps tend to be lower than those of single-channel retailers. Second, the exposure to more offline stores in the region leads to higher shopping app stickiness and usage time, suggesting that offline store presence affects mobile shopping behavior. The other variables of regional characteristics and weather are also significant. Third, consumers use shopping apps to a greater extent in the evening and on weekends. Furthermore, the effect of daily app usage time is positive and significant, which underlines the importance of controlling for overall mobile app usage. Lastly, we find that younger and female consumers shop mobile more, whereas affluent consumers visit shopping apps less frequently.

6.4 Magnitude of Social Media Influence on Mobile Shopping

We obtain the practical magnitude of the effect of social media app usage time on shopping app usage by overall using the estimates of the interaction effect model in Table 2. Specifically, we compute users' shopping app usage for different levels of broadcasting and narrowcasting app usage time, holding the remaining variables at their means. For a simple comparison, we use the scores of the bottom 10% and top 10% of social media app usage time of the observed data and simulate shopping app stickiness and usage time in the given conditions.

When usage time of broadcasting and narrowcasting apps increases from the values at the bottom 10% to the top 10%, the shopping app stickiness improves by 9.58% (from 0.237 to 0.260) and by 6.65% (from 0.240 to 0.256), respectively. On the other hand, shopping app usage time shows more dramatic changes due to the opposite main effects of both social media types. The same amount of increase in broadcasting app usage time results in increased shopping apps usage time by 13.95% (from 12.60 to 14.35), while the same increase of narrowcasting app usage time leads to decreased shopping app usage time by 8.53% (from 13.66 to 12.50).

The different magnitudes might call for the judicious implementation of social media apps as a marketing channel. For instance, reminding mobile shopping via any social media apps would be effective in improving shopping app stickiness and customer retention. However, if retailers want to increase customers' usage time per session, social media marketing focusing on broadcasting apps would be a better strategic choice than splitting the marketing budget across both broadcasting and narrowcasting apps.

7. Conclusion

Despite the prevalence of mobile shopping and the modern shift in social media channels to mobile phones, limited research has investigated the relationship between social media and mobile shopping in the context of mobile apps. To the best of our knowledge, our study is among the first to empirically explore the impact of social media app usage on shopping app usage. Specifically, this research investigates how social media apps influence shopping app usage by examining two distinct mobile app performance metrics (i.e., app stickiness and usage time). Furthermore, we deepen our understanding of the effect of social media by investigating two types of social media apps—broadcasting vs. narrowcasting apps.

Our main findings are as follows. Social media app usage increases shopping app stickiness regardless of the type of social media apps. Whereas broadcasting app usage increases shopping app usage time, narrowcasting app usage decreases it. Thus, depending on which types of social media apps consumers use before visiting a shopping app, usage time spent on a shopping app changes. Furthermore, as users are more likely to be engaged in offline social interactions, the effects of social media app usage on both shopping app stickiness and usage time weaken.

7.1 Theoretical Contributions

This research makes several theoretical contributions to the literature on mobile shopping and social media. First, in addition to our main contribution by investigating the relationship between social media apps and shopping apps, this research answers recent calls for more investigation on performance metrics for mobile apps. Despite the prevalence of mobile apps, there is limited research about performance metrics to understand mobile app usage behavior. Particularly regarding shopping apps and websites, purchasing as an outcome variable has been researched profusely (Dinner et al., 2015; Narang & Shankar, 2019), while the browsing behavior itself has not received as much attention. We focus on two mobile app performance metrics—shopping app stickiness and shopping app usage time—that are widely used in the field as key performance metrics in the mobile app context (Braze, 2016; McKinsey & Company, 2019).

Hardly any studies have differentiated the frequency of app visits (i.e., app stickiness) and app usage time, which are distinct behavioral indicators. App stickiness is more related to commitment to the retailer brand, while the usage time has more to do with the product assortment and purchase likelihood. This differentiation is subtle yet crucial in the current retail environment in which creating a retail brand is effortless and products are becoming abundant. Moreover, a handful of studies investigating app stickiness limit their scope to the relationship between characteristics of the app itself and the stickiness measure (Kim et al., 2016; Stocchi et al., 2020). Our study connects shopping app stickiness to the use of other types of apps (i.e., social media apps) and their influence.

Second, we acknowledge that distinct characteristics of two types of social media (i.e., broadcasting vs. narrowcasting apps) may result in different social media effects on mobile shopping. Some researchers have examined the different effects of two types of social media on consumers' perception and behavior (e.g., Barasch & Berger 2014; Foti et al., 2020). But they have focused on consumer behavior occurring within social media, such as sharing and distributing the content. Despite the overwhelming importance and diversification of social media apps in our daily lives, there is little-to-no research that examines differential effects of social media depending on types, particularly in the context of mobile apps. We contribute to the social media literature by distinguishing between two types of social media and examining their different effects on mobile shopping.

Finally, we contribute to the literature of social interactions by considering the moderating effect of offline social interactions in understanding the effect of social app usage (i.e., online social interactions) on shopping app usage. Although there have been some studies investigating the effect of offline social interactions on online shopping behavior (e.g., Choi et al., 2010; Iyengar et al., 2015), limited studies have examined the simultaneous effect of offline and online social interactions. For example, Toker-Yildiz et al. (2017) show that offline interactions with the same-office friends could offset the effect of online interactions in a company's platform for a wellness program. However, the study was conducted in the context of social interactions among employees in a single firm, rather than common social interactions through popular social media with anyone including friends and family. Using the mobile app usage data along with real-time location information, we show that offline social interactions, as well as online social interactions, have significant influences on shopping app usage. Thus, offline social interactions should be taken into account when researching the effect of social media in the mobile app usage context.

7.2 Managerial Implications

We provide strategic guidance and valuable insights into utilizing social media for shopping app management. First, recall that the effects of social media usage on shopping app stickiness differ from those on shopping app usage time; such effects also vary depending on types of social media apps (i.e., broadcasting vs. narrowcasting apps). These findings suggest that retailers may have to prioritize marketing goals, either enhancing customer retention (i.e., shopping app stickiness) or increasing usage time in their apps. Furthermore, they should acknowledge that not all social media platforms will be efficient in improving shopping app performance. For example, the positive association between social media app usage and shopping app stickiness suggests that marketing on any kind of social media platform will be efficient to increase shopping app stickiness. However, to increase shopping app usage time, broadcasting apps will be a better choice.

In addition, we provide managers practical guidance on how to utilize location-based targeting in social media for successful mobile marketing. For example, as offline social interactions increase, the effects of social media app usage of both kinds on shopping app stickiness weaken. Hence, to induce more revisits to a shopping app, sending location-based coupons via social media apps may outperform in regions with little in-person social interactions. On the other hand, when planning social media marketing in broadcasting apps to increase shopping app usage time, it may also work better to send geo-targeted mobile messages to regions with less offline social interactions than those with more offline social interactions.

7.3 Limitations and Suggestions for Future Research

Our research has some limitations that may serve as promising avenues for future research. First, although we have individual-level data on app browsing, we have no access to mobile transaction data and do not observe whether a consumer has purchased a product while using a shopping app. Future research can verify the impact of social media app usage on purchasing decisions in shopping apps by using mobile transaction data. Second, as a proxy measure of offline social interactions, we use the aggregated density of restaurants, cafes, and bars in all the regions visited within a day. We admit that it would be ideal to track whether a consumer is actually involved in offline social interactions (i.e., face-to-face communication) and what consumers were talking about during offline social interactions. Although we believe that the current measure of offline social interactions reasonably captures potential offline social interactions, future research may try different measures of offline social interactions, such as the number of accelerometer-defined steps referring to offline physical activity (Althoff et al., 2017) and intensity of check-ins based on location-based social network (Rizwan et al., 2018), and validate whether the moderating effect of offline social interactions remains significant. Third, the effect of social media app usage may differ across app categories (e.g., games, entertainment, travel, health, finance, etc.). A cross-category comparison would provide valuable insights into industry-specific social media marketing via mobile.

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Table 1. Summary Statistics

	Mean	SD
Dependent variables		
Shopping app stickiness	0.244	0.323
Shopping app usage time (in hours)	0.221	0.329
Independent variables		
Broadcasting app usage time (in hours)	0.144	0.283
Narrowcasting app usage time (in hours)	0.528	0.761
Offline social interaction	4.934	1.355
Control variables		
Premium (1: Stores selling luxury goods, 0: Otherwise)	0.059	0.235
Omni-channel (1: Omni-channel, 0: Otherwise)	0.883	0.321
Offline shop exposure	10.164	0.862
Public transportation	0.680	0.030
Floating population	100.516	35.905
Temperature	3.724	4.189
Precipitation	0.532	5.113
Evening (1: 6-12 p.m., 0: Otherwise)	0.329	0.470
Weekend (1: Weekend, 0: Weekdays)	0.263	0.440
Month – August (1: August, 0: Otherwise)	0.229	0.420
Month – September (1: September, 0: Otherwise)	0.203	0.403
Month – October (1: October, 0: Otherwise)	0.205	0.403
Month – November (1: November, 0: Otherwise)	0.215	0.411
Daily app usage time (in hours)	3.890	2.880
Age	31.028	9.430
Gender (1: Female, 0: Male)	0.583	0.493
Income (1: High, 0: Low)	0.404	0.491

Table 2. Estimation Results

Parameters	Main Effect Model				Interaction Effect Model			
	App Stickiness		Usage Time		App Stickiness		Usage Time	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Independent variables								
Broadcasting app usage time	0.053^{**}	0.005	0.074^{**}	0.005	0.355^{**}	0.018	0.172^{**}	0.019
Narrowcasting app usage time	0.014^{**}	0.002	-0.011^{**}	0.002	0.029^{**}	0.006	-0.026^{**}	0.007
Broadcasting app usage time × Offline social interaction					-0.060^{**}	0.003	-0.020^{**}	0.004
Narrowcasting app usage time × Offline social interaction					-0.004^{**}	0.001	0.002	0.001
Offline social interaction					-0.034^{**}	0.002	-0.044^{**}	0.002
Control variables								
Premium	-0.045^{**}	0.005	-0.073^{**}	0.006	-0.044^{**}	0.005	-0.072^{**}	0.006
Omni-channel	-0.334^{**}	0.004	-0.254^{**}	0.004	-0.326^{**}	0.004	-0.252^{**}	0.004
Offline shop exposure	0.004^{**}	0.002	-0.016^{**}	0.002	0.052^{**}	0.002	0.034^{**}	0.002
Public transportation	-0.726^{**}	0.044	-0.479^{**}	0.047	-1.105^{**}	0.045	-0.895^{**}	0.049
Floating population	0.000	0.000	0.000^{**}	0.000	0.000^{**}	0.000	0.000^{**}	0.000
Temperature	0.001^{**}	0.000	0.001^{**}	0.000	0.000	0.000	0.000	0.000
Precipitation	-0.001^{**}	0.000	-0.001^{**}	0.000	-0.001^{**}	0.000	-0.001^{*}	0.000
Evening	0.028^{**}	0.003	0.022^{**}	0.003	0.029^{**}	0.003	0.022^{**}	0.003
Weekend	0.015^{**}	0.003	0.041^{**}	0.003	0.009^{**}	0.003	0.038^{**}	0.003
Month – August	-0.022^{**}	0.004	-0.050^{**}	0.004	-0.024^{**}	0.004	-0.052^{**}	0.004
Month – September	-0.042^{**}	0.004	-0.064^{**}	0.005	-0.044^{**}	0.004	-0.066^{**}	0.004
Month – October	-0.046^{**}	0.004	-0.068^{**}	0.005	-0.049^{**}	0.004	-0.073^{**}	0.004
Month – November	-0.029^{**}	0.004	-0.040^{**}	0.004	-0.033^{**}	0.004	-0.045^{**}	0.004
Daily app usage time (in hours)	0.016^{**}	0.001	0.028^{**}	0.001	0.017^{**}	0.000	0.028^{**}	0.001
Age	-0.005^{**}	0.000	-0.001^{**}	0.000	-0.004^{**}	0.000	0.000	0.000
Gender (Female)	0.068^{**}	0.003	0.046^{**}	0.003	0.084^{**}	0.003	0.066^{**}	0.003
Income	-0.037^{**}	0.003	0.004	0.003	-0.035^{**}	0.003	0.004	0.003
AIC	12899		19613		11428		18525	

* indicates significance at $p < 0.05$ and ** indicates significance at $p < 0.01$

Figure 1. Conceptual Framework