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CONCEPTUAL/THEORETICAL PAPER

Personalized mobile marketing strategies

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Abstract

The prevalence of mobile usage data has provided unprecedented insights into customer hyper-context information and brings ample opportunities for practitioners to design more pertinent marketing strategies and timely targeted campaigns. Granular unstructured mobile data also stimulate new research frontiers. This paper integrates the traditional marketing mix model to develop a framework of personalized mobile marketing strategies. The framework incorporates personalization into the center of mobile product, mobile place, mobile price, mobile promotion, and mobile prediction. Extant studies in mobile marketing are reviewed under the proposed framework, and promising topics about personalized mobile marketing are discussed for future research.

Keywords Mobile marketing · Mobile personalization · Mobile marketing mix · Artificial intelligence

Introduction

During the past decade, the definition of "mobile" has rapidly evolved from describing mobile phone landscapes to more broadly encompassing a range of portable computing devices (i.e., tablets, wearables, and smart speakers) and mobile services (i.e., mobile applications [app] and virtual assistants) (Investopedia 2018). Mobile has reshaped the way marketers interact with customers and has created new marketing opportunities. Furthermore, the business potential of mobile marketing will exceed $183 billion within the next 5 years (BusinessWire 2019), and over half of the world's population will own at least one mobile device (Statista 2019).

Mobile marketing is set apart from other marketing strategies by its hyper-context personalized targeting. In other words, marketers can design and deliver highly relevant and personalized mobile targeting content through mobile channels (SMS, in-app, and push notifications) based on the instantaneous customer context of location, time, environment, companion, and dynamic competition. In the age of mass marketing, marketers leveraged conventional media channels such as TV and newspapers to design "one size fits all" advertising tactics. However, with the advent of the internet, marketers are armed with better insights into consumers' online behaviors and use this to conduct digital segmentation targeting. Further, the ubiquity of mobile devices gives marketers immediate access to customers' hyper-context information via mobile devices' built-in GPS, accelerometer, sensor, and gyroscope. The rich mobile data of behavioral and environmental contexts empower marketers to generate more adaptive and personalized pricing and promotion strategies. Emerging mobile channels and services such as the app, smart speaker, and mobile Vblog have more interactive features to engage customers and are considered more personal for users. Thus, mobile marketing extends the traditional marketing mix by introducing a central piece of personalization. Marketers are empowered to design more personalized mobile marketing by leveraging hyper-context insights: at which locations consumers are using their mobiles (where), what times they are looking for products (when), how they search for information and complete purchases (how), and whether they are alone or with someone else when using mobile devices (with whom). With unprecedented individual-level mobile data and prominent applications of artificial intelligence (AI) and deep

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learning algorithms, marketers can more accurately predict customer behaviors and uncover insightful patterns that could not be explored in the past.

Moreover, mobile devices integrate digital experience with offline behaviors, exposing new business opportunities. The success of the sharing economy depends largely on the prevalence of mobile usage. Uber, as a pure mobile app, satisfies real-time riding requests with dynamic pricing and optimal route assignment. Likewise, Mobike, a sharing bike company in Asia, fulfills commuters' last-mile gap needs by making shared bikes available near users through mobile geo-tracking data. Each bike is equipped with a smart lock, which enables riders to simply scan the QR code on the bike to unlock it and enable pedaling. Existing offline businesses also tap into mobile channels. For example, all major commercial banks in the U.S. now promote mobile payment apps because an increasing number of customers are adopting mobile wallets for convenience. Traditional brick-and-mortar stores are still valuable for shoppers who browse information on their mobile device and visit stores for inspection and the experience before making a purchase. Thus, store-first retailers design app-rooming[1] strategies to target mobile shoppers for store purchases. Mobile marketing offers considerable research opportunities across many domains such as the sharing economy, omnichannel shopping, mobile app, mobile payment and finance, mobile targeting, and mobile AI applications.

A burgeoning stream of academic research has developed in recent years to explore new mobile phenomena and consumer behavior changes. In a seminal article about mobile marketing, Balasubramanian et al. (2002) provided the first conceptualization of mobile commerce (here M-commerce) and discussed the implication of M-commerce from a space and time matrix. Barwise and Strong (2002) focused on the application of mobile marketing-permission-based short-message-service (SMS) ads and concluded that with the right execution, mobile advertising would benefit both advertisers and customers. These seminal efforts provide a preliminary understanding of emerging mobile behaviors in mobile commerce and SMS ads. Recently, researchers have applied field data to explore optimal mobile marketing effects with customer hyper-contexts such as location and weather (Andrews et al. 2016; Ghose et al. 2019a; Li et al. 2017; Luo et al. 2014). Scholars also strive to derive insights from detailed mobile data by applying machine learning algorithms to analyze customers' physical location trajectory and colocation networks (Ghose et al. 2019b; Zubcsek et al. 2017). An emerging stream of marketing research explores how customers interact with artificial intelligence (AI) mobile apps (i.e., chatbot) and smart devices (i.e., robot) in daily life, and how to implement AI algorithms for a better customer experience (Castelo and Thalmann 2019; Ciechanowski et al. 2019; Huang and Rust 2018; Leung et al. 2018).

At this point, it is worth acknowledging existing efforts in mobile marketing research and identifying new directions for future studies. It should be noted that this article does not provide a comprehensive analysis for each study on mobile marketing, as several articles offer more in-depth reviews and insights into mobile advertising (Grewal et al. 2016), promotion (Hui et al. 2016), gamification (Hofacker et al. 2016), and mobile shoppers (Shankar et al. 2016). Instead, we aim to offer a thematic review of past work and provide a coherent and comprehensive understanding of specific topics discussed by prior review papers (Hofacker et al. 2016; Hui et al. 2016; Shankar and Balasubramanian 2009; Shankar et al. 2016; Shankar et al. 2010). Extending the efforts of Grewal et al. (2016) on incorporating the environmental and technological context into customer-related characteristics, we develop a framework that highlights the central role of personalization in mobile marketing and organize extant research around the mobile marketing mix 5 Ps (product, place, price, promotion, and prediction). We also generate a forward-looking perspective to guide future research in the next phase of exciting mobile phenomena, contexts, and insights. In this way, we hope that our framework and thoughts in this article will help researchers to better understand the landscape of mobile personalized marketing and push forward research frontiers.

We begin our review of research by collecting and analyzing papers published in the major marketing journals (*Journal of the Academy of Marketing Science*, *Journal of Marketing*, *Journal of Marketing Research*, *Marketing Science, and Journal of Interactive Marketing*), the marketing section of *Management Science*, and mobile marketing related research in *Information System Research*. We research relevant studies in each journal by detecting keywords that include any combination of "mobile," "app," and "m-commerce" on EBSCO. Then, we review the topic and method of each paper to guarantee that the selection is marketing related and applies either field data or customer survey data for their analyses (we exclude conceptual papers and papers with analytical/structural models). We also review the reference lists of each paper to identify additional articles. Consequently, we select 33 articles published between 2002 and 2019 in the abovementioned journals. One key feature of these mobile marketing articles is the large sample size: 23 out of the 33 articles have a sample size larger than 5000. A detailed paper summary is attached in Appendix Table 2. As mobile marketing combines various forms of consumer hyper-context information (e.g., location, time, environment) to design personalized targeting ads, a large sample size enables researchers to explore heterogenous effects across diverse consumer groups.

The remainder of this paper is organized as follows. In the next section, we introduce the framework and present the

[1] App-rooming is an omnichannel shopping behavior whereby customers search for product information on the merchant's mobile app and visit the merchant's offline store for purchases.

process through which marketers could transform contextual data into personalized marketing strategies. We then review the literature and business practices around each element of the mobile marketing mix in the framework and highlight promising future research directions. We conclude our review and discussion in the last section.

A framework for personalized mobile marketing

The central piece in our proposed framework of mobile marketing is personalization, galvanized by granular contextual insights at the individual customer level (Fig. 1). Mobile gives marketers a deep understanding of customer hyper contextual factors such as physical location, temporal information, cross-channel behaviors, surrounding environment, shopping companion, and market competition. Moreover, personalized mobile marketing is concerned about incorporating marketing planning into the customers' shopping contexts to satisfy individual customer heterogenous needs. Mobile devices enable marketers to track both the customers' virtual mobile search behaviors and physical movements at offline locations (where), and target shoppers with promotions at the right time when they are considering different options and are about to purchase (when). This data allows marketers to understand customers' cross-channel shopping behaviors and offer seamless shopping experience with omnichannel targeting (how). Moreover, the network information of a mobile device signal enables marketers to capture extensive information about customers' surrounding environment with other mobile users. This mobile network information is a powerful tool for targeting customers since a shopping decision can be affected by social peer preference and shopping companions (with whom). Businesses have seen pronounced success with personalized mobile targeting. Through social media listening and customer search intent, the marketing team of Nike identified tremendous interests in the teams of Nigeria, France, and Brazil before the 2018 World Cup. Building on the deep insights from customer profiles and shopping interests across channels, the marketing team designed a personalized World Cup campaign to target customers with different ages, regions, and digital channels (e.g., YouTube, Snapchat, and WhatsApp, etc.) with different ad contents, leading to enormous customer product interests and discussions. The Nigeria team collection jersey was sold out within 3 h after release (Fast Company 2018; Quartz 2018).

The marketing mix concept proposed by McCarthy (1960) focuses on physical products and promotions with the conceptualization of the 4 Ps. As mobile marketing evolves from a product-dominant to a service-dominant view (Vargo and Lusch 2004), the mobile marketing mix also shifts to promote customer-centric personalization. By deriving insights from the customers' contexts, we extend the traditional market mix concept to the mobile marketing mix of mobile product, mobile place, mobile pricing, mobile promotion, and mobile prediction. Mobile products include both smart portable devices that can interactively respond to customers' requests and virtual services that satisfy customers' demand on-the-go.

Mobile devices are on the rise as a critical channel for social interactions and commercial transactions, and mobile activities also have spillover effects across different

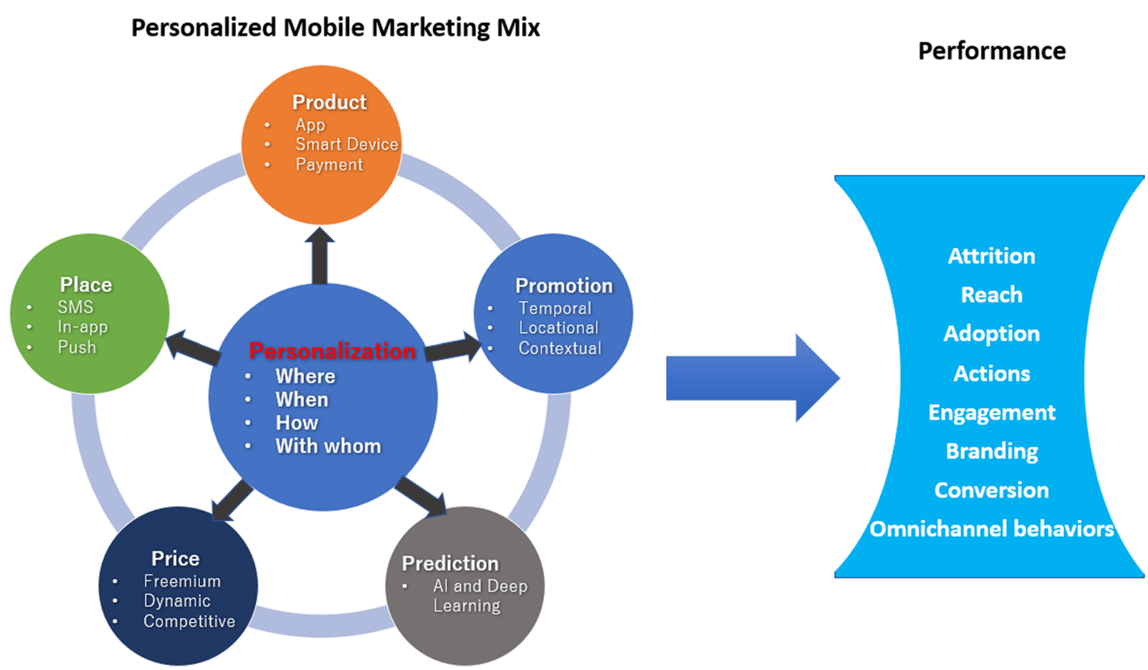

Fig. 1 Research framework

channels. Mobile devices incorporate both a virtual information search and physical travel trajectory, providing a seamless online to offline experience. With such rich information about the customers' contextual factors and behavioral intentions, marketers are able to craft dynamic promotion and pricing strategies that are more adaptive to individual personalized needs. Applying insights with customer geo-location information, Macy's targets potential customers around the stores with in-store discount promotions to drive foot traffic. Uber applies sophisticated algorithms to compute the optimal resource allocation based on the number of ride requests and free drivers on the road. Thus, the company can charge customers a higher rate at peak times and a lower rate during flat hours, a pricing strategy that fully depends on the dynamic status of customers' willingness to pay and market supply.

Designing a mobile marketing mix centered on personalization not only boosts the performance of mobile campaigns but also more precisely gauges campaign results. Moving beyond the immediate and direct evaluation of digital clicks and attrition, mobile marketers can continuously track the customers' response to the marketing efforts online and offline and estimate short- and long-term omnichannel impact. In addition, marketers can evaluate mobile campaigns' reach, attrition, and adoption more efficiently by identifying unique mobile identity. Efforts have been invested to engage and retain mobile app users with push notifications after they download an app. For example, by offering a free 30-day trial for existing free app users, Spotify can estimate how many new sign-ups of paid users are generated from this mobile campaign. Furthermore, mobile marketers emphasize long-term customer relationships and customer life value across various shopping channels. The Nielsen Company now provides a cross-screen ad measurement tool that combines TV, desktop, and mobile to calculate in-store sales (Digitalnewsdaily 2018). Zara evaluates the performance of its mobile augmented reality app with sales from both online and offline channels (Retaildive 2018). More importantly, mobile evolves as an integrated piece in customer shopping journey, and each component of mobile 5 Ps interacts with one the other to affect the performance of mobile campaigns. To attract younger generation of movie audience for the newest movie "Spider Man: Far From Home", Sony Pictures initiates a social media campaign on Snapchat by allowing users to take selfies with the framed webslinger at designated locations through the Snapchat AR lens (Mobile Marketer 2019). This campaign not only drives the awareness and social buzz around the movie but also nurtures a long-term relationship between young social media users and Spider Man movie series.

Next, we will review each component of the mobile marketing mix and connect extant research progress with future directions (a summary is in Table 1).

Mobile product

Mobile products include both hardware mobile devices and virtual mobile applications and are rapidly transforming into digital services to satisfy customers' personal needs through m-commerce, mobile apps, mobile social, mobile streaming, mobile wallet, and virtual assistants. M-commerce is an emerging business model wherein business communications and activities are conducted on mobile devices (Balasubramanian et al. 2002), and it provides customers with the flexibility of any-time, any-place access to browse products and make purchases. According to the data shown from Statista.com, more than 50% of ecommerce now takes place on mobile devices (Statista 2018). Mobile apps account for nearly 50% of global internet traffic, and there are over 197 billion app downloads in 2017 (Businessofapps 2018; Themanifest 2018). Customers use mobile apps every day to connect with friends, make purchases, gain access to information, and make payments. With the development of wireless signal infrastructure, social interactions and video streaming are shifting dramatically from PC to mobile platforms (Digital Trends 2018). New mobile platforms combining social elements with streaming content have attracted considerable popularity and a significant number of downloads. The Vblog app TikTok rose to No. 2 in app downloads with more than 30 million active users in the U.S. within 3 months of its debut (eMarketer 2019). In addition, payment terminal devices and mobile technologies such as near field communication (NFC) enable customers to manage funding and transfer money digitally with a mobile wallet. Mobile payment is becoming increasingly popular because it is fast, secure, and convenient. Apple and Google have both launched and promoted their own mobile wallet, and customers enjoy the benefits of convenience of "tap-to-pay" with their mobile devices at stores. In addition, mobile virtual assistants such as Alexa and Google Assistant have become 24-h personal butlers that help users handle daily errands and provide updated information.

To design a more personalized product experience, marketers first need to understand how customers perceive new mobile products and adopt them for usage. Moreover, marketing scholars have a long-standing interest in how customers respond to emerging mobile products and services. Early research into mobile marketing started almost two decades ago when mobile devices were only considered useful for communication through voice and text medium. Nysveen et al. (2005) classified mobile services as text messaging, contact, payment, and gaming. They developed a theoretical model to explain consumers' intention to use mobile services and concluded that consumers' usage intention was affected by motivational influences (usefulness, ease of use, and usage enjoyment), attitudinal influences, social influences (peer/social pressure), and resource-related influences (consumers' perceived control of usage).

Table 1 Existing literature and future research focus

Mobile Marketing Mix	Existing Paper	Future Research Direction
Mobile Product	• Mobile Service Adoption (Nysveen et al. 2005) • Mobile Content Consumption (Ghose and Pil Han 2011; Grewal and Stephen 2019) • Mobile commerce (Einav et al. 2014) • Mobile App (Ghose and Pil Han 2014) • Mobile Wallet (Economides and Jeziorski 2017) • Mobile keyword search (Wang et al. 2019) • Mobile Content Generation (Melumad et al. 2019)	1) How does social influence affect mobile product adoption and usage? 2) In what context does a customer have fewer concerns about privacy when using mobile products? 3) How does multiscreen usage affect customer responses to brand mobile ads? 4) How do people conduct shopping differently through smart devices and virtual assistants (i.e., Amazon Echo and Google Assistant) relative to online or in-store? 5) Do the mobile wallets change customer price perceptions and willingness to pay? 6) As customers have more interactions with emerging mobile products and services, what new metrics can marketers apply to evaluate customer engagement?
Mobile Place	• SMS marketing (Barwise and Strong 2002) • Mobile microblogging (Ghose et al. 2013) • Mobile display banner (Bart et al. 2014) • Mobile usage in offline shopping (Hui et al. 2013; Grewal et al. 2018) • B2B mobile engagement (Gill, Sridhar, and Grewal et al. 2017) • Channel switch and cross-channel impact (de Haan et al. 2018; Xu et al. 2014; Xu et al. 2017)	1) How do customers consume information differently on mobile channels relative to other channels? 2) How can brands utilize Vblog and augmented reality services to drive customer engagement? 3) What are the unique shopping features of app-rooming compared to web-rooming? 4) What role will smart devices play in the future for the customer shopping journey? 5) What are major challenges for customers in the shift from mobile shopping to voice shopping with smart devices? 6) How will mobile channels reshape business-to-business relationships and affect the firms' value?
Mobile Price	• Mobile Freemium (Arora et al. 2017) • Mobile price elasticity (Kübler et al. 2018) • Competitive pricing (Fong et al. 2015) • Geo-targeting pricing (Dubé et al. 2017)	1) To what degree should marketers offer free mobile products and services to acquire most paid users? 2) Should marketers apply a uniform price strategy between PC and mobile channels or different price strategies to achieve optimal business performance? 3) How would price surge and discounts of real-time mobile services (such as Uber) affect the demand and supply of the service in the short term and long term? 4) Will information access through mobile ease or intensify price discrimination across channels?
Mobile Promotion	• Mobile coupon redemption (Danaher et al. 2015) • Mobile targeting promotion with temporal and locational information (Luo et al. 2014; Fong et al. 2015) Mobile behavioral targeting promotion (Fong et al. 2019) • Mobile promotion with surrounding environment (Andrews et al. 2016; Ghose et al. 2019b) • Mobile promotion with weather (Li et al. 2017)	1) How will customers respond to promotion in a negative context environment such as a traffic jam and air pollution? 2) How can marketers apply the insights of real-time customer emotions to design of mobile promotions? 3) What are the potential downsides of mobile promotions on customers' cross-channel shopping behaviors? 4) How will social referral incentives drive mobile purchases? 5) How do mobile promotions affect customers' subsequent search and purchase?
Mobile Prediction	• Mobile geo-similarity network (Provost et al. 2015) • Dynamic Colocation network (Zubcsek et al. 2017) •Customer in-store trajectory (Ghose et al. 2019b) •Copycatting app identification (Wang et al. 2018)	1) What are the potential measurements that marketers can apply in algorithm predictions? 2) What insights can marketers attain by applying algorithms to voice and video data? 3) How do customers perceive the recommendation and targeted content generated from algorithm predictions? 4) What is the impact of algorithm bias on marketers' decision-making? 5) Will algorithm predictions increase customer welfare? 6) How will Mobile 5Ps interact with each other and affect the performance of mobile campaigns?

Recent research also explores what characteristics app users care about the most regarding the download decision. Ghose and Pil Han (2014) applied a structural econometric model to estimate customer preferences toward different app features. They documented that the app description length, number of screenshots, the age of app, number of apps by the same developer, number of previous versions, and volume and valence of app reviews all positively influenced the app demand; in contrast, the file size of the app had a negative influence on the app demand. They also showed that in-app purchase options had a positive impact on the app demand, which was equivalent to offering a 28% price discount for the app. However, in-app advertisement options had a negative impact on app demand and the effect was equivalent to increasing the app price by 8%. Vlachos and Vrechopoulos (2008) explored consumers' intention to use mobile services. They found that content quality, contextual quality, device quality, connection quality and privacy concerns have a strong positive influence on service quality perceptions and behavioral intention. Kim et al. (2015) showed that the adoption of a brand's mobile application raised brand purchase behaviors. Spaid and Flint (2014) qualitatively investigated reasons that customers used mobile devices while shopping and found that mobile devices provided assistance for shopping management and social management behaviors.

Moreover, marketers need to acquire a deeper understanding of consumers' behavior and consumption differences in mobile products and services compared to other digital and traditional ones. Researchers have explored behavioral differences between mobile and internet content consumption. Ghose and Pil Han (2011) identified the unique behavioral characteristics of user-generated content and content consumption with mobile devices. Leveraging more than 2.3 million data records from 180,000 mobile users in South Korea, they found temporal negative interdependence between mobile content generation and consumption, suggesting that content generation on mobile devices required a higher level of effort and more resources than PC content consumption. Moreover, people were more likely to engage in content usage than content generation when traveling, and their content usage behaviors were also affected by social network neighbors. Ghose et al. (2013) applied mobile data from microblogging to examine users' mobile browsing behaviors. They found that ranking effects were stronger for mobile content because high-ranking links were more likely to be clicked on mobile screens, and geographic proximity was more important for mobile browsing. These results indicated that search cost is higher and travel distance matters for mobile content browsers. Wang et al. (2019) conducted field studies and lab experiments, consistently finding that a paid keyword in a mobile setting could induce higher direct sales than in an online setting, although it generated lower indirect sales in general. Moreover, while keyword costs attenuate the positive relationship between mobile search and direct sales, keyword specificity and keyword cost attenuate the negative relationship between mobile searching and indirect sales. Shen et al. (2016) found that mobile shopping may increase the choice of hedonic products due to the touch interface of mobile devices, compared with shopping on a desktop computer with a mouse. These findings suggest that mobile users behave differently compared to PC users in terms of content consumption. Applying a large set of field data and several lab studies, Grewal and Stephen (2019) found that customers have higher purchase intentions after being informed that the review was created with mobile devices. In addition, Melumad et al. (2019) showed that content generated on a smartphone (vs. PC) is in general more emotional because people tend to prioritize emotional information when writing shorter content. Similarly, Ransbotham et al. (2019) indicated that word of mouth content generated through mobile devices was more affective and concrete. However, people tended to have lower perceived value for mobile generated content over time.

Furthermore, recent studies examine the long-run impact of mobile products on customer engagement and welfare. Kumar et al. (2018) indicate that mobile-based digital payment will enhance customer engagement, and the effect is moderated by market, firm and customer factors. Economides and Jeziorski (2017) studied the impact of mobile money in Tanzania with a natural experiment involving an unexpected increase in transaction fees. They categorized mobile money activities into money transfer to others, money transportation for short distances, and money storage. The results suggested that customers were willing to pay transaction fees for mobile money activities, implying that mobile money could reduce crime-related risks.

Researchers have also focused on the downsides of mobile products, such as privacy. Xu et al. (2012) noted that perceived control over personal information is a key factor affecting consumers' context-specific concerns for information privacy, which may be enhanced by assurance approaches, such as individual self-protection, industry self-regulation, and government legislation. Personalization can both enhance and diminish consumer engagement with the firm: it may elicit privacy concerns because consumers worry about how their data are collected and used. Consumers' perceptions regarding privacy threats in the mobile environment are also influenced by country of origin and personal profiles (Gurău and Ranchhod 2009). Thus, firms should use the personal information in a strategic manner to balance such a personalization-privacy paradox (Aguirre et al. 2015; Grewal et al. 2017).

Future research agenda Despite substantial efforts to explore customer adoption and the usage of mobile products, many important topics remain untouched by current research. For example, as mobile products connect friends, colleagues, and families in virtual social networks, social factors should play an important role in their adoption and usage. Moreover, customers are more concerned about privacy and information protection in a mobile context as devices collect continuously users' personal information. Mobile privacy and trust could be another essential topic. In addition, it is becoming critically important to interpret how customers interact with brands in the context of multiscreen shopping wherein customers may use mobile and other channels simultaneously for different tasks. Furthermore, it is worth exploring how mobile services such as virtual assistant and mobile wallet affect customers' decision-making and the shopping process. Therefore, we propose the following opportunities for future research: (1) How does social influence affect mobile product adoption and usage? (2) In what context does the customer have fewer concerns about privacy when using mobile products? (3) How does multiscreen usage affect customer responses to brand mobile ads? (4) How do people conduct shopping differently through smart devices and virtual assistants (i.e., Amazon Echo and Google Assistant) relative to online or in-store? (5) Do mobile wallets change customers' price perceptions and willingness to pay? (6) As customers have more interactions with emerging mobile products and services, what new metrics can marketers apply to evaluate customer engagement?

Mobile place

Mobile channels represent not only a medium for information delivery (i.e., SMS, in-app ad, push notification, live streaming, and smart speakers) but also include the dynamic interactions when customers use mobile services and products in the physical world for information search and purchases. On the one hand, the ubiquity of mobile devices in brick and mortar stores enables customers to easily access product information and explore promotions. On the other hand, marketers have a better access to customers' purchase intent with mobile search and trajectory data when they travel in the store, offering ample opportunities to target in-store shoppers for product browsing and impulsive purchases. Thus, mobile channel is becoming a hub across digital channels and physical locations (Harvard Business Review 2017). Despite a smaller screen size and higher search costs, information search on mobile devices grew more than 80% year over year in 2017 (Adweek 2018). Customers spend more than 5 h a day on their mobile devices, and most of that time is spent on media consumption and information searches (Bluecorona 2018). The beauty brand Sephora recognizes the importance of personalized digital experiences and incorporates the virtual experience with the in-store shopping journey by adaptively designing promotion content based on the customers' own Beauty Bag product collections (Hubspot 2018; Zinrelo 2018).

Mobile devices create various interactive features that enable brands to communicate with customers in a more personalized and timely manner. The relatively small screen size and privacy concerns of mobile devices remind marketers to implement mobile-friendly design and explore optimal content design. In recent decades, mobile channels have evolved from pure text messaging and static mobile display banners to personalized mobile coupon and dynamic app push notifications. Several empirical studies in the field have been undertaken to nurture the knowledge of different mobile channels. Barwise and Strong (2002) provided a seminal discussion about how firms could adopt SMS text messaging as a communication medium to reach target audiences. They found that an audience had a positive response to SMS communication if the brand obtained the explicit permission of the audience to send brand information.

As customers spend more time on mobile devices for content consumption, it is important to examine how mobile channels can drive business performance. Ghose et al. (2013) explored potential opportunities for mobile microblogging. They found that because mobile devices had a smaller screen with higher search costs for customers, ranking effects were stronger for mobile phones. Their analyses showed that moving one position up on microblogging would lead to a 37% increase for the click-through rates on the post, which was 12% higher than the increase caused by a one position movement upward on computers.

Due to size constraints, the mobile display banner contains limited information about the product function and specifications, which reduces the effectiveness of communications. Thus, not all product categories are suitable to be communicated through mobile channels. Bart et al. (2014) applied a large dataset that featured 54 mobile display campaigns across three years to explore which type of product was best suited to the mobile display banner. Their analysis showed that the mobile display banner had a significantly positive effect on raising the customers' favorable attitudes and purchase intention for utilitarian products with a higher involvement. Mobile display banners remind customers of previous product-specification information, and utilitarian products with high involvement are more likely to trigger memory recall.

A rich body of research has investigated how mobile channel usage affects customers' shopping patterns and purchase decisions in other digital channels. Wang et al. (2015) indicated that the adoption of mobile shopping affected online shopping behaviors. Leveraging a large dataset of eBay mobile app users, Einav et al. (2014) documented several findings about the impact of m-commerce adoptions on internet commerce. They concluded that the early adopters of m-commerce were also heavy users of ecommerce in the past, and purchases made via mobile were different from those made on the regular website as mobile was used more for browsing. More importantly, they found that mobile purchases were also associated with an overall business boost and were incremental to the overall growth. Xu et al. (2014) empirically examined customers' response to the introduction of the mobile apps of Fox News. Their results suggested that the mobile app complemented the mobile web channel because the adoption of the mobile app led to increased news consumption and more traffic to the web channel. The complementarity effect was stronger for customers who had a focused preference for media consumption with fewer time constraints.

Customer interactions with mobile channels also affect physical shopping behaviors. Hui et al. (2013) conducted a field experiment at a grocery store and empirically tested the relationship between in-store travel distance and unplanned purchases. They found that sending a mobile coupon that requires customers to travel a longer distance from their planned path resulted in a significant increase in unplanned spending. Grewal et al. (2018) used eye-tracking technologies in their studies to identify mobile usage during the shopping process and showed that mobile usage at stores lead to higher overall spending. They proposed that mobile usage was a distraction for shoppers, resulting in more time spent in-stores to browse products and check prices in nonconventional shopping paths.

From a business channel perspective, mobile substantially reshapes the way companies engage with corporate buyers. Mobile business-to-business (B2B) apps are designed to facilitate business communications, project collaborations, purchase and order, and business relationship management. However, assessing the sales impact of B2B mobile apps is challenging as sales performance is influenced by numerous business initiatives. Applying a difference-in-differences specification and matching strategy to data from a tool manufacturer, Gill et al. (2017) estimated the effect of B2B app adoption on sales growth. They found that the buyers who adopted the B2B app created more projects using the app and generated higher revenue for the company. The average annual sales lift by the app is between 19.11% and 22.79%.

From a channel portfolio perspective, scholars have examined whether the advent of mobile acts as a complementarity or substitution to existing channels. Leveraging archive data from Alibaba with a natural incidence of iPad app introduction by the company, Xu et al. (2017) examined how the emergence of tablet usage would influence customers' behaviors on smart phones and PCs. They found that the introduction of a tablet app engendered an incremental $923.5 million annual revenue growth. The adoption of the tablet spurred browsing behaviors, which led to more impulsive purchases and a wider range of products being considered by customers. They also concluded that tablets acted as a substitute for PCs but served as a complement for smartphones because the purchase of PC channels dropped and the purchase of smartphone channels increased after the adoption of tablets. De Haan et al. (2018) explored the effects of device switching by using clickstream data from an online retailer. They found a positive impact on the purchase conversion rate when customers switched from a more mobile device (such as a smartphone) to a less mobile device (such as a computer), and the effect was stronger for expensive and risky product categories. The authors argued that purchasing from a less mobile device provided customers with safe transaction environment, which reduced the perceived risk related with the product and purchase process.

Future research agenda New mobile channels are on the rise with the proliferation of live streaming, augmented reality, and smart devices. The interactive and personal features of mobile channels are encouraging researchers to cultivate comprehensive insights into customer behavioral patterns in these new channels. In addition, there is little empirical evidence about how marketers can operate these channels for product display and communication. Furthermore, mobile devices and offline stores have become an integrated piece during customers' omnichannel shopping journeys. Customers conduct both deal-hunting showrooming activities and on-the-go mobile searches during store visits through app-rooming. Thus, it is vital to grasp the influence of mobiles in omnichannel shopping. Moreover, the launch of brand apps could have a profound impact on a firm's valuation and reform business-to-business processes, leading to unexplored interdisciplinary domains in business management and finance. We propose several new avenues for future research: (1) How do customers consume information differently on mobile channels relative to other channels? (2) How can brands utilize Vblog and augmented reality services to drive customer engagement and purchases? (3) What are the unique shopping features of app-rooming compared to web-rooming? (4) What role do smart devices play in the future of the customer shopping journey? (5) What are the major challenges for customers shifting from mobile shopping to voice shopping with smart devices? (6) How can mobile channels reshape business-to-business relationships and affect firms' value?

Mobile price

Freemium and dynamic pricing are two essential mobile pricing strategies. Marketers can apply flexible pricing strategies to promote mobile products/services and attract new customers. Freemium[2] models offer potential customers free opportunities to experience products before making purchases. One important question to address is how the free version of mobile services will affect the paid version. Applying a unique dataset with 7.7 million observations from more than 12,000 paid apps, Arora et al. (2017) noted that freemium had negative effects on the performance of paid versions. They found that offering free versions of paid apps had negative associations with the adoption speed of paid apps. This negative

[2] App developers offer basic functions of the app for free and charge a fee for premium functions.

effect was stronger for hedonic apps that provided fun and pleasure at a later life stage of a paid app. Furthermore, in the early life stage of paid apps, the developers' reputation had a stronger positive association with the adoption speed than did user ratings. However, Ghose and Pil Han (2014) documented that offering both free and paid versions increased the overall demand for the app, and the number of apps by the same developer had a positive impact on app demand.

Marketers may also apply insights of customer price sensitivity for adaptive mobile price discrimination. Kübler et al. (2018) estimated how cultural, economic, and structural factors affect the sensitivity of app demand to price changes. They acquired the top 20 selling apps in 60 countries during a 267-day period. They categorized countries based on the Hofstede Index, operationalized the economic status with GDP per capita and the Gini index of income inequality, and decomposed structural factors such as age, education, and mobile penetration. They found that price sensitivity was indeed heterogenous across different countries and that people had a higher price sensitivity in countries with higher masculinity and uncertainty avoidance. These findings offer practical implications for marketers to consider cultural and economic factors that influence customers' price sensitivity to mobile products when designing price strategies across different markets.

Mobile devices capture customers' locational and purchase information, which facilitates marketers in designing flexible pricing strategies in the competition for geo-conquesting. An optimal pricing strategy is to acquire competitors' customers without cannibalizing profits from existing customers. Fong et al. (2015) examined geo-conquest pricing targeting customers at a competitor's location with different price levels in a field experiment. They designed three targeting locations (the focal theater location, the competitor location, and a neutral location as a benchmark) with three price schemes (low, moderate, and high discount level). Their analyses indicated that targeting customers at a competitor's location with moderate and high price discounts led to higher purchase rates; however, targeting customers at the focal theater's own location with a high price discount would cannibalize profits from existing customers as there was no increase in purchase rates compared with the medium discount level. Dubé et al. (2017) further discussed the geo-targeting pricing strategy (geo-fencing and geo-conquesting) by considering competitors' strategic response. By manipulating the geo-targeting promotion strategies of two competing theaters, they confirmed that targeting customers close to the focal theater's location (geo-fencing) raised the purchase rate, and the conversion rate increased from 0.5% without promotion to 4% with a 40% price discount. They also showed that targeting customers at the competitor's location (geo-conquesting) was profitable and the conversion rate was 3% with a 60% price discount. However, if competitors responded to a focal firm's geo-targeting pricing with a similar defensive price scheme (geo-fencing) to target its own customers, the incremental profit by the geo-targeting pricing of the focal theater would be wiped off in the equilibrium.

Future research agenda Emerging mobile marketing contexts promote a substantial transformation for mobile pricing from conventional static promotion to real-time dynamic price discrimination. However, the relationship between free mobile services and paid versions are still underexplored. More research is needed to explore the underlying economic theory to explain customers' decision-making between free and paid mobile services. Moreover, businesses are engaging with customers through different channels and devices, and it is becoming more challenging to design an optimal pricing scheme across various channels and devices. Recently, Netflix tested a cheaper price strategy on the subscription of its mobile version in the overseas market (The Verge 2019). Ride sharing platforms apply dynamic pricing to ease increasing demand during peak hours and stimulate extemporaneous supply. However, such strategies may also have a negative impact on social welfare due to strategic rider and driver behaviors. We propose several directions for future research: (1) To what degree should marketers offer free mobile products and services to acquire the most paid users? (2) Should marketers apply a uniform price strategy between PC and mobile channels or different price strategies to achieve optimal business performance? (3) How would price surge and discounts of real-time mobile services (such as Uber) affect the demand and supply of the service in the short term and long term? (4) Will information access through mobile ease or intensify price discrimination across channels?

Mobile promotion

With the advent of mobile technologies that incorporate locational, temporal, and environmental information, marketers could design and implement novel mobile promotion campaigns. "One size fits all" is replaced by personalized promotions with the individual customer's purchase history, preference, and timing. By diving into customers' listening history and "thumb up" behaviors, the music app Pandora promotes customized music collections fitting individual preferences. With granular and timely mobile trajectory movement data, marketers can accurately detect customers' proximity to the store and even their in-store shopping trajectory for better contextual promotion targeting. Marketers can also personalize ad copy and promotion content based on an individual customer's mobile search, shopping preferences, and mobile behaviors. Home Depot designs the content of app push notifications for in-store promotions based on the app users' present in-app product search behaviors.

Applying fine-grained in-app behavior data, Fong et al. (2019) explored the potential crowd-out effects of mobile targeting on a reading app. They found that targeting customers based on individual behaviors might increase the sales of the promoted products and similar products but hurt sales of dissimilar products. Such crowd-out effects of targeting promotion are due to targeted ads reducing customer search behaviors in nontargeted product categories. To examine how timing and location of sending mobile coupon promotions affects the redemption rate, Danaher et al. (2015) conducted a field experiment in a large shopping mall and found that "mobile coupons are all about time and location." The analyses indicated that sending coupons in the morning led to a higher redemption rate and coupons sent on Monday and Thursday had a significantly higher redemption rate than sending coupons on Wednesday did. Customers were also more likely to redeem coupons if they were close to the store offering the coupon. Luo et al. (2014) tested the mobile promotion effectiveness with a combination of temporal and locational factors. They designed a randomized field experiment with three temporal targeting treatments (same-day, one day prior, or two days prior) and three locational targeting treatments (near, medium, or far). They found that geo-targeting promotion and temporal targeting promotion individually increased the sales probabilities; however, the results of combining these two strategies were not straightforward. Targeting proximal customers with same-day promotional offers led to higher sales incidences than targeting them with the offer two days earlier. Similarly, Fong et al. (2015) found that targeting customers who were close to stores generated higher same-day sales and purchases on subsequent days. The economic impact of geo-targeting promotions were substantial: targeting store-proximal customers generated 6 times more purchases than targeting customers who were not close to stores, and 12 times more purchases than not targeting store-proximal customers.

Based on 14,972 mobile users in a large-scale field experiment with the world's largest telecom providers, Andrews et al. (2016) explored the potential impact of mobile promotion in the physical crowdedness context on customers' response to ads. Innovatively, they acquired real-time physical crowdedness by gauging the number of active mobile users on the subway train. Their analyses suggested that the response rate to the mobile promotion was higher when targeting commuters on a crowded subway train versus targeting those on an uncrowded subway train. The response rate was 2.1% when there were fewer than two people per square meter on the train and would increase to 4.3% with five people per square meter. These results were robust to sudden variations in crowdedness caused by unexpected train delays and street closures. A plausible explanation to the positive response rate for the crowded subway train is that mobile immersion as crowdedness invaded personal private space and people tended to focus inward and were more responsive to mobile promotion. Ghose et al. (2019b) explored mobile promotion effectiveness when customers were on public transportation. Collaborating with a commuting app company, they conducted a field experiment to target commuters and noncommuters with mobile coupons. They found that targeting commuters would increase the rate of coupon redemption, and the redemption rate was three times higher when targeting commuters compared with targeting noncommuters. Moreover, sending coupons with a shorter expiration window had a better effect. They proposed that the chronic stress from routine commuting might lead commuters to be more responsive to mobile coupons with a short duration. Extant findings about the positive effect of comfortlessness and stress on mobile promotion response reveal an interesting idea that mobile ads could be a welcome relief for customers in uncomfortable contexts.

In addition, mobile targeting promotion could be incorporated with broader environmental factors such as weather. To test how weather conditions could impact customer responses to mobile promotions, Li et al. (2017) conducted a field experiment with more than 6 million mobile users. They exploited purchase responses in various weather conditions such as sunny, rainy, and cloudy, and accounted for weather variations with both backward-looking historical weather conditions and forward-looking weather forecasts. Their results indicated that customers were more responsive and made purchases more quickly in sunny weather compared to cloudy weather; however, responses were lower and slower in rainy weather. Furthermore, they also explored the second-order interactive effects between weather and ad copies and concluded that prevention ad copy would hurt the purchase response boost in sunny weather, but it mitigated the response drop in rainy weather.

Future research agenda Customer responses to mobile promotions are largely dependent on the surrounding environment and psychological conditions. There are abundant opportunities to further investigate how marketers can better incorporate personalization into promotion designs. With accelerometers, emotion detection, and facial recognition techniques being incorporated into smart devices, mobile promotions can integrate with various individual physical and emotional characteristics such as anxiety and excitement, opening up new interdisciplinary research opportunities with psychology and sociology. Moreover, mobile promotions not only affect customer behaviors on mobile channels but also spill over into other digital and physical channels, resulting in more complicated estimations about the overall impact of mobile promotions. In addition, researchers should also consider the dark side of mobile promotions in terms of customer lifetime value and firm long-term valuation. Potential directions for future studies are: (1) How will customers respond to promotions in negative contexts such as a traffic jam and air pollution? (2) How can marketers apply the insights of customers' real-time emotions in designing mobile promotions? (3) What are the potential downsides of mobile promotions for customers cross-channel shopping behaviors? (4) How will social referral incentives drive mobile purchases? (5) How will mobile promotions affect customers' subsequent search and purchases?

Mobile prediction (with machine learning and AI)

Marketers are empowered by the fine-grained mobile data with locational, temporal, environmental, and social factors to predict variations in individual behavioral patterns at the granular level. Mobile devices capture contextual information and customers behaviors, which enable marketers to understand customers' intention, stage of purchase path, decision-making process, and instant needs. However, mobile data contain various types of unstructured formats, requiring more sophisticated methods for analyses and interpretations. With the advancement of machine learning and deep learning algorithms, marketers can now attain in-depth insights to design personalized mobile targeting strategies and make predictions of customer behaviors. We have seen studies exploring the effect of mobile targeting which has been implemented in various contexts with different promotion contents (Grewal et al. 2018; Hui et al. 2013; Fong et al. 2015; Ho and Lim 2018). Next, we will introduce several papers that move toward predictions and personalization.

Since mobile users typically interact with multiple devices, marketers need to find effective ways to pinpoint the same user across different devices for personalized marketing and predictions. In a design-science paper, Provost et al. (2015) built a geo-similarity network to identify same and similar mobile users based on a detailed location-visitation data. The geo-similarity network was constructed by weighting the link between devices based on shared locations. The network could help marketers identify different entities corresponding to the same individuals across screens. Moreover, the geo-similarity network could also link users with similar behavioral browse interests, which are critical for mobile personalization and prediction. By applying the proposed network design in field data, they found that neighbors identified by the network were more likely to visit similar websites, suggesting a substantial lift in prediction power. Zubcsek et al. (2017) proposed that customers' historical location choices might be informative for understanding their product preferences. They constructed a dynamically evolving colocation network that contained events, wherein multiple participants were at the sample location at the same time. Their techniques of constructing the colocation network combined both static location network methods and dynamic methods for studying customers' movement patterns. The results supported their proposition that there was, indeed, a positive relationship between collocated customers' preferences for the same product category. Incorporating customers' colocation information could improve the prediction accuracy for conversion by 19%.

The improvement of location tracking precision by mobile devices now allows marketers to capture dynamic customers' movement trajectory within a specific location. Using the fine-grained behavioral data of the customers' physical movement path, Ghose et al. (2019b) proposed a novel trajectory-based mobile targeting strategy. To construct customers' movement trajectory, the authors applied a machine learning algorithm to extract temporal duration, spatial dispersion, semantic information, and movement velocity features from a large-scale user-level field behavioral data. They then computed the similarity between each two-individual pair of the movement trajectory and clustered customers into groups based on trajectory similarity. The mobile targeting strategy to recommend a specific store was designed based on the visit frequency by similar mobile users in the trajectory group. The empirical results showed that trajectory-based mobile targeting leads to a higher redemption rate and revenues for stores compared with conventional targeting strategies. Moreover, trajectory-based targeting not only improved the efficiency of customers' current shopping process but also induced them to change their future shopping patterns.

Another application for machine learning predictions is to automate the process of mobile analyses. Wang et al. (2018) apply a combination of machine learning algorithms with natural language processing, latent semantic analysis, and network-based clustering to identify copycatting apps. They first defined copycats based on functionality and appearance similarity and further classified copycats into deceptive and nondeceptive types. The authors applied the detection results to a sample of 10,100 action game apps by 5141 app developers and estimated the impact of copycats on the demand for original apps. They found that both the quality and level of deceptiveness of the copycat affected the demand for the original app. The results showed that high quality nondeceptive copycats had a negative effect on the demand for the original app, whereas low quality deceptive copycats had a positive effect on the demand for the originals.

Future research agenda The potential of AI in mobile predictions is promising. AI has existed for several decades, but past few years have seen some major breakthroughs with the development of deep learning. AI algorithms are applied in prediction and customer analytics. Businesses implement AI algorithms to unify sophisticated data structures pulled from multiple sources simultaneously and uncover granular individual level insights by identifying the unique pattern for each customer. Companies such as Amazon use AI to predict purchase behaviors and make recommendations to their customers. With AI and machine learning, apps can be programmed to have a certain "human-like" ability by enabling them to reason for themselves without any real human intervention. Thus, AI-powered mobile apps can identify individual customers' needs and desires and provide a more personalized experience. Netflix applies AI algorithms to capture video watching behaviors across millions of users and designs new TV shows based on the algorithm predictions for the film director, leading actors, and story content. Many brands utilize the Facebook Message chatbot app to engage with customers and generate insights about their purchase intent.

However, AI algorithms are created by humans and could suffer subjective human bias during the programming process. Information acquisition and insight generation via computer algorithms may not reflect the ground truth. Moreover, customers still prefer to interact with humans and may push back against AI programs due to algorithm aversion. Scholars could invest more effort investigating topics concerning customer response to mobile computer programs. Questions for future research include: (1) What are the potential measurements marketers can apply in algorithm predictions? (2) What insights can marketers attain by applying algorithms to voice and video data? (3) How do customers perceive the recommendation and targeted content generated from algorithm predictions? (4) What is the impact of algorithm bias on marketers' decision-making? (5) Will algorithm predictions increase customer welfare? (6) How will Mobile 5Ps interact with each other and affect the performance of mobile campaigns?

Conclusion

As mentioned in the introduction, this article does not aim to offer an extensive review for existing work at mobile marketing domains, as we choose articles from a select set of journals. Our work concerning personalized mobile marketing complements prior efforts that synthesize specific topics in mobile marketing (Grewal et al. 2016; Shankar and Balasubramanian 2009; Shankar et al. 2010) or discuss mobile as a topic in a broader digital context (Kannan and Li 2017; Lamberton and Stephen 2016). In this article, we construct a framework to review extant efforts on mobile marketing and discuss relevant applications in business practices. We have seen a proliferation of mobile topics in the marketing research domain with the integration of various methods. Moreover, new research is emerging with a combination of machine learning and artificial intelligence applications alongside. An increasing number of studies involve large-scale datasets and apply sophisticated models and algorithms. However, we also identify a lack of broader connection among extant efforts with the marketing 4Ps. Few efforts have been put forth to understand how the mobile 5Ps interact with each other and ultimately influence the performance of mobile campaigns. Thus, it is critical that we consolidate the fragmented work into our framework and foster a holistic view of mobile marketing mix centered around personalization.

By reviewing the extant studies and business practices under our framework, we organize our thoughts to discuss each P in mobile marketing. We offer a forward-looking outlook on several promising topics and trends for scholarship in the near future. These insights extend the boundaries of mobile marketing and explore the future technologies and algorithm applications that will affect marketing practices. With the introduction of more connected and intelligent mobile devices, future research can generate unprecedented insights about customers' psychological and behavioral patterns. With the support of AI, researchers can handle more complicated data structures that contain subtle information about customers that were undetectable in the past. Nevertheless, this does not mean that behavioral research or theoretical work has less value in the future; conversely, the mobile marketing domain needs studies with behavioral and theoretical methodologies to explain the psychological factors for mobile products and services adoption, omnichannel shopping decisions, responses to mobile ads in micro contexts, and attitudes toward dynamic pricing. Finally, we hope that this paper motivates future research to explore impactful topics and contribute to this rapidly growing domain of personalized mobile marketing.

Appendix

Table 2 Summary of the literature

Mobile Marketing Mix	Authors	Topic	Data	Data Source	Sample Size	Performance Outcome
Product	Nysveen et al. 2005	Adoption of Mobile Service	Survey Data	Online survey	1000-5000	Perceived attitude
Product	Ghose and Pil Han 2011	User Generated Content and Content Usage	Field Data	Mobile service company	>5000	Frequency of content downloads, uploads, and visits
Product	Ghose and Pil Han 2014	Demand for Mobile App	Panel data	App stores	1000-5000	App downloads
Product	Economides and Jeziorski 2017	Mobile Wallet	Field Data	Mobile carrier	>5000	Transactions of mobile money
Product	Wang et al. 2019	Mobile Keyword Search	Field and Lab data	e-Commerce website	<1000	Direct and indirect sales
Product	Melumad et al. 2019	Mobile User Generated Content	Field and Lab data	Yelp	>5000	Mobile content emotionality and emotional valence
Product	Grewal and Stephen 2019	Mobile Review	Field and Lab data	Tripadvisor	>5000	Perceived review credibility and purchase intentions
Place	Barwise and Strong 2002	SMS Marketing	Survey Data	The Mobile Channel	<1000	Surveyed satisfaction
Place	Dickinger and Kleijnen 2008	Mobile Coupon Redemption	Survey Data	Online Survey	<1000	Intention to coupon redemption
Place	Ghose et al. 2013	Mobile Browsing Behavior	Field Data	Microblogging	<1000	Mobile click-throughs
Place	Einav et al. 2014	Adoption of Mobile Commerce	Field Data	eBay	>5000	Platform purchases
Place	Bart et al. 2014	Mobile Display Advertising	Field data	Market Research Agency	>5000	Customer favorable attitude and purchase intentions
Place	Xu et al. 2014	Channel Impact	Panel survey	Comscore	>5000	News consumption on mobile web
Place	Gill, Sridhar, and Grewal et al. 2017	B2B Engagement on Mobile App	Field Data	A leading manufacturer	<1000	Business sales
Place	Grewal et al. 2018	In-store Shopping and Mobile Usage	Field Experiment	Retail stores	<1000	Customer purchase volume
Place	de Haan et al. 2018	Channel Switch	Field Data	Online retailer	>5000	Conversion rate
Place	Xu et al. 2017	Channel Impact	Field Data	Alibaba	>5000	Customer spending
Price	Arora et al. 2017	Mobile App	Field Data	Google Play	>5000	Adoption of mobile app
Price	Kübler et al. 2018	Mobile App Popularity	Field Data	App stores	>5000	Price and rating sensitivity
Price	Fong et al. 2015	Mobile Competitive Locational Targeting	Field Experiment	Mobile carrier	>5000	Coupon redemption
Price	Dubé et al. 2017	Mobile Targeting Coupon	Field Experiment	Mobile carrier	>5000	Coupon redemption
Promotion	Hui et al. 2013	In-store Unplanned Purchase	Field Data	Grocery store	<1000	Unplanned store spending
Promotion	Danaher et al. 2015	Redemption of Mobile Phone Coupons	Field Data	Shopping mall	>5000	Coupon redemption
Promotion	Luo et al. 2014	Mobile Targeting Promotion	Field Experiment	Mobile carrier	>5000	Coupon redemption
Promotion	Fong et al. 2015	Dynamic effects of Location-based Mobile Promotion	Field Experiment	Mobile carrier	>5000	Contemporaneous and delayed mobile purchase
Promotion	Andrews et al. 2016	Mobile Targeting with Crowdedness	Field Experiment	Mobile carrier	>5000	Coupon redemption
Promotion	Li et al. 2017	Mobile Promotion with Weather	Field Experiment	Mobile carrier	>5000	Mobile purchase rate
Promotion	Ghose et al. 2019b	Mobile Targeting during Transportation	Field Experiment	Mobile App	>5000	Coupon redemption
Promotion	Fong et al. 2019	Mobile behavioral targeting	Field Experiment	Mobile App	>5000	Cross-category consumption
Prediction	Provost et al. 2015	Geo-similarity Network	Field Data	RTB system	>5000	Visits to the same publisher
Prediction	Zubcsek et al. 2017	Predict Mobile Coupon Redemption based on Colocation	Field Data	Mobile carrier	<1000	Coupon redemption
Prediction	Ghose et al. 2019b	Mobile Targeting with Locational Trajectory	Field Experiment	Shopping mall	>5000	Coupon redemption
Prediction	Wang et al. 2018	App Copycat	Field Data	iOS App Store	>5000	Copycat app detection

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