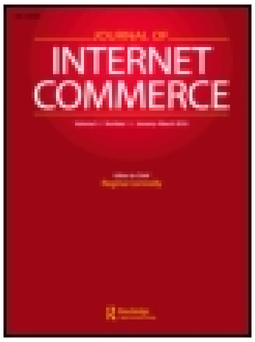

Journal of Internet Commerce

ISSN: 1533-2861 (Print) 1533-287X (Online) Journal homepage: http://www.tandfonline.com/loi/wico20

An Exploratory Study of Mobile Shopping Behaviors of Young Adults in Thailand

Ngan N. Chau, Srivatsa Seshadri, Greg Broekemier & Santikorn Pamornpathomkul

JOURNAL OF INTERNET COMMERCE
https://doi.org/10.1080/15332861.2018.1463802

An Exploratory Study of Mobile Shopping Behaviors of Young Adults in Thailand

Ngan N. Chau[a], Srivatsa Seshadri[a], Greg Broekemier[a], and Santikorn Pamornpathomkul[b]

[a]Department of Marketing & MIS, University of Nebraska at Kearney, Kearney, Nebraska, USA; [b]Faculty of Business Administration, Rajamangala University of Technology Thanyaburi, Pathum Thani, Thailand

ABSTRACT

Smartphone users in Thailand are among the most active in Southeast Asia. Thailand is also ranked the fifth-best nation in Eastern Asia in terms of ease of doing business, making it attractive for both domestic and global companies. Given the paucity of studies on mobile shopping behaviors among Thai users, this study attempts to examine different aspects of those behaviors—such as shopping and information search activities—and the associated factors using a sampling frame of a Thai university. The analysis yields important implications for marketers who are interested in developing a mobile presence in this emerging market.

KEYWORDS
Mobile commerce; mobile shopping; segmentation

Introduction

Mobile devices, particularly smartphones, have increasingly become an important means to access the Internet and conduct online activities. According to eMarketer (2016), Thai smartphone users are among the most active in Southeast Asia, spending about 160 minutes per day on smartphones. Further, according to a January 2017 data release from the National Statistical Office of Thailand, more than 90% of Internet users in the country go online via smartphones. The popularity of such mobile devices provides a plethora of opportunities for online businesses to pursue; in fact, eMarketer (2017) projects that retail e-commerce sales in Thailand will hit $5.7 billion by 2020.

In addition, according to Maloney (2017), Thailand is investing heavily to improve its position as one of Southeast Asia's primary gateways for commerce. Besides its strong manufacturing sector, this nation of 68 million people has a low cost of living and a business-friendly environment: It is ranked the fifth-best nation in Eastern Asia in terms of ease of

CONTACT Ngan N. Chau chaunn@unk.edu Department of Marketing & MIS, University of Nebraska at Kearney, 1917 West 24th Street, WSTC 400C Kearney, NE 68849, USA.

doing business. With strong environmental support, Thailand is attractive not only for domestic marketers but also for global companies.

Despite the many positive attributes of the Thai market, there is a paucity of empirical work relating to the adoption of mobile commerce in Thailand. In a recent study, Krairit (2018) found that among the four identified Internet user types in Thailand, only one group—the nonuser group—is similar to previous work published in the area; the other three are groups that only recently emerged and are completely different from the typologies identified in past studies. This strongly implies that there have been changes in the patterns of Internet usage in Thailand.

Further, with the rapid growth of commercial activities on mobile devices (i.e., mobile commerce or mobile shopping), we believe it is important to better understand consumer behaviors on these devices in Thailand. Here, mobile shopping refers to the process of acquiring product information, goods, and services using mobile devices. The purpose of our study is to explore different aspects of behaviors on mobile devices that are relevant to mobile shopping—such as activities engaged in and information search—and to identify factors that may be associated with such behaviors. In particular, we focus on young adults ranging from 18 to 37 years old (born around 1980–1994); this group is identified as potential mobile device shoppers around the world (Ström, Vendel, and Bredican 2014). Further, given their relatively young ages, these consumers are especially attractive for marketers who are seeking lifelong brand-loyal customers; through building brand loyalty among them early on, marketers may be able to sustain long-term revenue streams for their brands.

The remainder of this article is organized as follows. The next section provides a review of the literature related to this study. In the third section, we discuss the methodology used. Results from our analysis are provided in the fourth section. Finally, we conclude the paper after a discussion of the implications of the results.

Literature review

This article is closely related to research on information technology acceptance and mobile marketing. The former originated in the long-studied information systems research (e.g., Davis 1989, 1993; Davis, Bagozzi, and Warshaw 1989), while the latter has recently emerged with the popularity of mobile technology and devices (e.g., Shankar and Balasubramanian 2009; Shankar et al. 2016). The following will review the literature on each of them.

Research on information systems has made substantial progress in understanding how individuals adopt new information technologies; numerous models have been developed to explain attitude, intention, and actual use of information technology. The technology acceptance model proposed by Davis (1989), for instance, suggests that perceived ease of use and perceived usefulness can be good predictors of technology usage; subsequent work (e.g., Venkatesh and Davis 2000) augmented the original model with other constructs such as subjective norm, experience, and voluntariness (also see King and He 2006 for a review). In 2003, the seminal work from Venkatesh et al. (2003) combined eight different models from psychology and sociology to derive the unified theory of acceptance and use of technology (UTAUT) model applied for organizational context. This model includes three predictors of intention (i.e., performance expectancy, effort expectancy, and social influence) and two determinants of usage (i.e., intention and facilitating conditions).

In an effort to extend the UTAUT model to the consumer use context, Venkatesh, Thong, and Xu (2012) added hedonic motivation, price value, and habit to the existing framework. Several empirical studies have been conducted to validate the UTAUT model and its extension in a wide range of products and cultural settings as reviewed by Williams, Rana, and Dwivedi (2015), but few validation studies of the UTAUT model have been conducted in Thailand, for example, Kijsanayotin, Pannarunothai, and Speedie (2009). In a recent study, Blaise, Halloran, and Muchnick (2018) investigated factors influencing purchase intentions in the context of mobile commerce; their data collection, however, was conducted only in the US. Our work extends the existing frameworks on acceptance and use of technology to another country with a high-context-culture setting for the adoption of mobile commerce. Based on the identified constructs from extant literature, we have adapted and generated various items for measurement in the context of mobile shopping; Table 1 summarizes our development of key items used in this study.

The second related stream of research is the one on mobile marketing. It focuses on "the two- or multi-way communication and promotion of an offer between a firm and its customers using a mobile medium, device, or technology" (Shankar and Balasubramanian 2009, 118). As noted by Shankar et al. (2010), mobile devices could provide a paradigm shift in retailing, allowing retailers to enter the consumer's environment anytime, anywhere. Wang, Malthouse, and Krishnamurthi (2015) observed changes in spending behaviors of consumers upon adopting mobile shopping (e.g., the number of orders increased); further, behavioral change varied from habitual to less routine purchases. Recently, Shankar et al. (2016) argued that mobile-based marketing activities could influence a shopper "along and beyond the path-to-purchase: from the initial shopping trigger, to the purchase, consumption, repurchase, and recommendation stages" (37) and

Table 1. Summary of item generation.

Construct	Definition	Sample of items generated
Performance expectancy	The degree to which using a technology will provide benefits to consumers in performing certain activities (Venkatesh et al. 2003, Venkatesh, Thong, and Xu 2012)	I find mobile shopping useful/Mobile shopping helps me save time/Mobile shopping increases my chances of getting special offers (e.g., discounts) and lower prices/ Mobile shopping is a convenient way to shop/Mobile shopping allows me to avoid interaction with salespeople/I find online product reviews useful/Mobile ads provide me with useful information
Effort expectancy	The degree of ease associated with consumers' use of technology (Venkatesh et al. 2003, Venkatesh, Thong, and Xu 2012)	Learning how to shop on mobile devices is easy for me/The process of shopping on mobile devices is clear and understandable/It is easy for me to become skillful at mobile shopping/Overall, I think mobile shopping is simple
Hedonic motivation	The fun or pleasure derived from using a technology (Childers et al. 2001, Venkatesh, Thong, and Xu 2012)	Mobile shopping is fun/Mobile shopping is enjoyable/Mobile shopping is very entertaining
Facilitating conditions	Consumers' perception of the resources and support available to perform a behavior (Venkatesh et al. 2003, Venkatesh, Thong, and Xu 2012)	I have an Internet-enabled mobile device to shop/I have reliable access to the Internet to shop on my mobile device/I have the resources to purchase products or services on a mobile device (e.g., credit card or other forms of mobile payment)/I have the knowledge necessary to shop on mobile devices/I can get help from others when I have difficulties shopping on mobile devices
Social influence	The degree to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology (Venkatesh et al. 2003, Venkatesh, Thong, and Xu 2012)	People who are important to me think I should use mobile devices for shopping/My friends think I should use mobile devices for shopping/My family members think I should use mobile devices for shopping/I don't want others to know what I am purchasing
Trust in mobile shopping	The willingness of a consumer to be vulnerable to the actions of an Internet merchant in an Internet shopping transaction, based on the expectation that the Internet merchant will behave in certain agreeable ways, irrespective of the ability of the consumer to monitor or control the Internet merchant (Mayer, Davis, and Schoorman 1995; Lee and Turban 2001)	Overall, I trust mobile shopping/I think the information on shopping sites/apps is honest and reliable/I believe those who sell on the Internet would carry out transactions faithfully/I believe those who sell on the Internet would keep their promises (such as fill my order correctly, deliver products on time, and provide after-sale services)/I trust online product reviews
Behavioral intention	Intentions to engage in mobile shopping (Venkatesh et al. 2003, 2012)	I intend to shop using mobile devices in the future/I expect to spend more time shopping on mobile devices in the future/I intend to make a higher percentage of my purchases using mobile devices in the future/I intend to use online product reviews more frequently in the future/I will write product reviews to aid others

proposed a comprehensive framework that synthesized multiple aspects of the "mobile" and "shopper marketing." Grewal et al. (2016) generated another important development in mobile marketing. Their mobile advertising effectiveness framework highlights the impact of seven elements in this area: context, consumer, ad goal, ad elements, outcome metrics, market, and firm factors.

Particularly relevant to our research is the framework proposed by Shankar et al. (2010); these authors argued that the effects of the "mobile" on consumer activities varied across consumer segments. Hence, it may be helpful to examine various consumer segments based on their usage of mobile devices (i.e., activities engaged in on a regular basis). Our identified segments, however, differ from theirs because we focus on young adults (18–37 years, born around 1980–1994) in another country: Thailand. Furthermore, we performed market segmentation to identify these segments from our data collection.

Overall, our study addresses new areas of mobile marketing and examines mobile usage activities to better understand young adults in Thailand. Many constructs used in our empirical work are adapted from the extended UTAUT model and other technology acceptance models.

Methodology

This study was conducted on a sample of students from a state university in Thailand; the campus where the data were collected is located in Pathum Thani province, about 30 km north of Bangkok, the capital and most populous city of Thailand. The questionnaire used in our study was developed in English by a group of researchers in the United States based on previous work and the researchers' expertise. A back-translation process was used to generate the questionnaire in Thai. More specifically, the English version was translated into Thai by language specialists at the university in Thailand. The outcome then was back-translated, evaluated, and compared with the original English version by another researcher who is fluent in both Thai and English. Subsequently, further modifications of the first version in Thai were made.

Questionnaires were delivered to students pursuing business programs in their classrooms. Participation was completely voluntary and students were provided paper-and-pencil surveys in Thai. A total of 346 students completed the survey; among those, 341 students were in the age range of 18 to 37. Since this study focuses on young adults, the analysis was conducted on this age group only. A summary of our sample profile is provided in Table 2.

Various measures were used in the study such as mobile device ownership, activities on mobile devices, search behaviors for more than 10 product categories, and factors influencing the adoption of mobile shopping (see

Table 2. Sample descriptive statistics.

Demographic profiles	Frequency	Percentage
Gender[a]		
Female	262	77%
Male	79	23%
Total	341	100%
Age		
18–22	293	86%
23–27	36	11%
28–32	8	2%
33–37	4	1%
Total	341	100%
Major		
Accounting	48	14%
Economics	47	14%
Finance	95	28%
Information system	4	1%
International business	9	3%
Management	37	11%
Marketing	101	30%
Total	341	100%
Class standing		
First year	30	9%
Second year	116	34%
Third year	98	29%
Fourth year	75	22%
Graduate	22	6%
Total	341	100%

[a]The gender makeup matches well with the business program participation profile at the university where the survey was conducted; e.g., as of 2016, gender makeup was 72% females and 28% males.

Table 3. Mobile device ownership.

	Female ($n = 262$)		Male ($n = 79$)		Total (n = 341)	
Device owned	Count	Percentage	Count	Percentage	Count	Percentage
Smartphone	254	97%	70	89%	324	95%
Laptop	105	40%	38	48%	143	42%
Tablet	32	12%	12	15%	44	13%
Other	2	1%	0	0%	2	1%

Table 1). Chi-square tests, analysis of variance, and a clustering technique were employed in our analyses.

Research results

Sample characteristics

Device ownership

Mobile devices were classified into four categories: laptop, smartphone, tablet, and other. More specifically, 95% of respondents owned a smartphone, followed by 42% owning a laptop and 13% owning a tablet (see the last column in Table 3). In terms of the number of devices owned, each respondent

Table 4. Mobile purchase experience.

	Female ($n=262$)		Male ($n=79$)		Total ($n=341$)	
	Count	Percentage	Count	Percentage	Count	Percentage
No purchase on mobile devices	21	8%	16	20%	37	11%
Less than 1 year	40	15%	14	18%	54	16%
1–5 years	155	59%	36	46%	191	56%
More than 5 years	46	18%	13	16%	59	17%
Total	262	100%	79	100%	341	100%

owned at least one device. It was noted that 197 (58%) owned one device, followed by 116 (34%) and 28 (8%) owning two and three devices, respectively. In other words, nearly one-half of the sample were multi-device owners.

Many independence tests were conducted between device ownership and gender. While there were no significant differences across gender in terms of the number of devices owned and laptop/tablet ownership, we found that smartphone ownership tended to vary across gender (p value for Fisher's exact test = .006). More specifically, a higher proportion of females owned a smartphone.

Purchase experience

Next, we investigated purchase experience on mobile devices (see Table 4). Thirty-seven (11%) respondents had made no purchases, whereas the rest (89%) had some experience. The majority of them (56%) had 1 to 5 years of experience. Further, purchase experience varied across gender, χ^2 (3) = 10.653, $p = .01376$. We then created two subgroups: those with and without experience (304 vs. 37 respondents) and found that females tended to have greater purchase experience than males did, χ^2 (1) = 9.3977, $p = .0022$.

Activities engaged in

Table 5 summarizes the top 10 activities that respondents engaged in one or more times on a typical day. Social networking and general information search were the most popular activities. Note that searching for information to make purchases had a very low rank (number 9), with 32% engaged in such activity. Although most of these activities were gender-neutral, females were more likely than males to engage in search to purchase, χ^2 (1) = 10.255, $p = .0014$.

Of interest, checking email tended to be dependent on mobile purchase experience, χ^2 (1) = 4.9602, $p = .0259$; while 43% of respondents with mobile purchase experience engaged in this activity, a lower percentage (24%) without such experience checked email on a regular basis. Another association was found between multi-device ownership and four activities (i.e., checking email, search for purchase, watching videos, and schoolwork).

Table 5. Activities engaged in on a regular basis.

		Female ($n = 262$)		Male ($n = 79$)		Total ($n = 341$)	
	Activity	Count	Percentage	Count	Percentage	Count	Percentage
1	Social networking	241	92%	70	89%	311	91%
2	General search	224	85%	62	78%	286	84%
3	Watching videos	178	68%	51	65%	229	67%
4	Playing games	145	55%	51	65%	196	57%
5	Texting	149	57%	44	56%	193	57%
6	Schoolwork	134	51%	37	47%	171	50%
7	Reading	110	42%	39	49%	149	44%
8	Checking email	111	42%	30	38%	141	41%
9	Search to purchase	112	43%	18	23%	130	38%
10	Getting directions	84	32%	26	33%	110	32%

Table 6. Activities engaged in and device ownership.

		Single-device ownership ($n = 197$)		Multi-device ownership ($n = 144$)		Chi-square tests	
	Activity	Count	Percentage	Count	Percentage	χ^2 (1)	p value
1	Checking email	66	34%	75	52%	11.843	.0006
2	Search for purchase	63	32%	67	47%	7.464	.0063
3	Watching videos	113	57%	116	81%	20.292	<.0001
4	Schoolwork	82	42%	89	62%	13.553	.0002

Table 7. Common product categories involved in information search.

		Female ($n = 262$)		Male ($n = 79$)		Total ($n = 341$)	
	Product category	Count	Percentage	Count	Percentage	Count	Percentage
1	Clothing	180	69%	31	39%	211	62%
2	Movies	146	56%	52	66%	198	58%
3	Food and beverages	127	48%	31	39%	158	46%
4	Games	102	39%	47	59%	149	44%
5	Travel services	120	46%	27	34%	147	43%
6	Music	102	39%	37	47%	139	41%
7	Books	67	26%	29	37%	96	28%
8	Transportation services	43	16%	14	18%	57	17%
9	Electronics	37	14%	16	20%	53	16%

Table 6 summarizes the relationship as well as the results from Chi-square tests.

Product search

Because general information search was popular among respondents (84% engaged in this activity on a regular basis), it is useful to examine information search behaviors in various product categories (see Table 7 for common categories). The majority of respondents were involved in searching information about clothing and movies (62% and 58%, respectively). Further, females tended to search for clothing, χ^2 (1) $= 22.334$, $p < .0001$, while males were more likely to search for games, χ^2 (1) $= 10.431$, $p = .0012$.

Table 8 illustrates the association between the likelihood of searching for various product categories and mobile purchase experience/device

Table 8. Product search, purchase experience, and device ownership.

Purchase experience	No ($n = 37$)		Yes ($n = 304$)		Chi-square tests	
	Count	Percentage	Count	Percentage	χ^2 (1)	p value
1 Clothing	13	35%	198	65%	12.5820	.0004
2 Travel services	9	24%	138	45%	5.9711	.0145
3 Music	21	57%	118	39%	4.3970	.0360
Multi-device ownership	No ($n = 37$)		Yes ($n = 304$)		Chi-square tests	
	Count	Percentage	Count	Percentage	Chi-square	p value
1 Electronics	21	11%	32	22%	8.4724	.0036
2 Travel services	63	32%	84	58%	23.558	<.0001
3 Books	46	23%	50	35%	5.3188	.0211
4 Movies	104	53%	94	65%	5.3262	.0210
5 Transportation services	23	12%	34	24%	8.5135	.0035

ownership. While the likelihood to search for clothing and travel services went up with purchase experience, the opposite direction was observed in music. It appears that owning more than one mobile device tended to raise the likelihood of searching for electronics, travel services, books, movies, and transportation services.

Activity-based segments

The top 10 activities engaged in on a daily basis were used to construct segments. We conducted cluster analysis using poLCA, an R package for polytomous variable latent analysis (Linzer and Lewis 2011). The number of clusters was selected based on the Bayesian information criterion (BIC) and the Akaike information criterion (AIC); as a result, our preferred model that minimizes values of the BIC (BIC = 3,883.5) and AIC (AIC = 3,760.9) consisted of three clusters.

The above outcome corresponds to three identified segments: (1) light users, (2) moderate users, and (3) heavy users. The star diagram in figure 1 compares these segments across activities engaged in. The shape of each segment is constructed from the proportions who selected corresponding activities (see Table 9 for specific numbers). Next, to assess the heterogeneity of the cluster solution, we conducted multiple Chi-square tests on each activity and found statistical significance across segments (i.e., p values $<$ .00001), indicating that heterogeneity had been achieved.

A description of different behaviors in the three identified mobile device user segments is provided below:

1. Light users: This segment consisted of 114 individuals (33% of the sample). These users were relatively inactive; on average, each of them engaged in 2.93 different activities (out of 10 activities listed) on a daily basis. The majority engaged in social networking (79%) and searching general information on the Internet (57%).

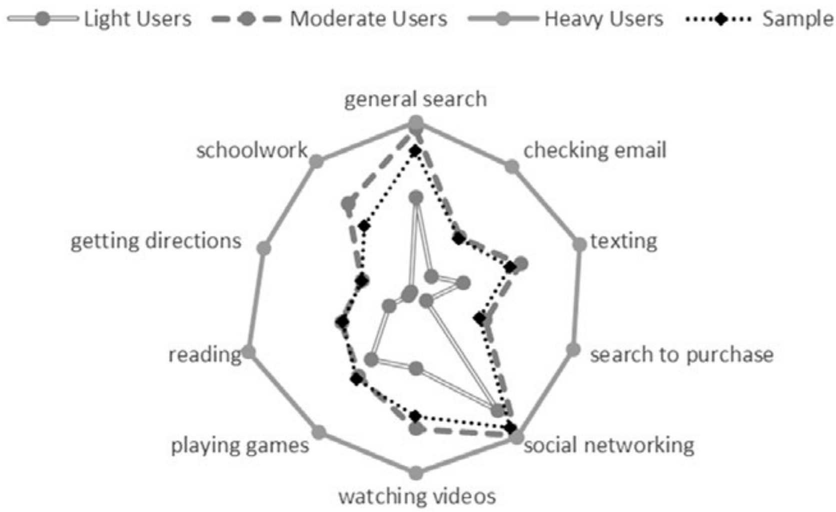

Figure 1. Segment comparison across activities engaged in.

Table 9. Activities engaged in each segment.

		Segment						Sample	
		1		2		3			
	Variable	Count	Percentage	Count	Percentage	Count	Percentage	Count	Percentage
1	Social networking	90	79%	168	97%	53	98%	311	91%
2	General search	65	57%	167	97%	54	100%	286	84%
3	Watching videos	46	40%	129	75%	54	100%	229	67%
4	Playing games	49	43%	96	55%	51	94%	196	57%
5	Texting	32	28%	108	62%	53	98%	193	57%
6	Schoolwork	5	4%	114	66%	52	96%	171	50%
7	Reading	18	16%	77	45%	54	100%	149	44%
8	Checking email	17	15%	74	43%	50	93%	141	41%
9	Search to purchase	7	6%	72	42%	51	94%	130	38%
10	Getting directions	5	4%	56	32%	49	91%	110	32%
	Cluster name	Light users		Moderate users		Heavy users			
	Size (%)	114 (33%)		173 (51%)		54 (16%)		341 (100%)	

2. Moderate users: The second segment was the biggest group, with 173 individuals (51% of the sample); on average, each of them performed 6.13 activities on a daily basis. In addition to social networking (97%) and general information search (97%), these users were likely to engage in watching videos (75%), schoolwork (66%), texting (62%), and playing games (55%).
3. Heavy users: The third segment was the smallest, with 54 individuals (16% of the sample). On average, each conducted 9.65 activities; in other words, these users engaged in almost all activities listed.

Segment profiles

To profile the identified segments, we examined various measured characteristics including gender, class standing, purchase experience, device

Table 10. Device ownership and product search by segment.

	Segment							
	Light users		Moderate users		Heavy users		Chi-square tests	
	Count	Percentage	Count	Percentage	Count	Percentage	χ^2 (2)	*p* value
Device owned								
1 Smartphone	103	90%	168	97%	53	98%	7.9573	.0187
2 Laptop	39	34%	73	42%	31	57%	8.1074	.0174
3 Tablet	8	7%	24	14%	12	22%	7.8315	.0199
Multi-device ownership	32	28%	81	47%	31	57%	15.9625	.0003
Product search								
1 Clothing	56	49%	114	66%	41	76%	13.5640	.0011
2 Movies	48	42%	112	65%	38	70%	18.4487	.0001
3 Food and beverages	27	24%	93	54%	38	70%	39.9004	<.0001
4 Games	43	38%	73	42%	33	61%	8.4701	.0145
5 Travel services	26	23%	89	51%	32	59%	29.8038	.0000
6 Music	40	35%	72	42%	27	50%	3.4811	.1754
7 Books	24	21%	55	32%	17	31%	4.2698	.1183
8 Transportation services	9	8%	28	16%	20	37%	22.4249	<.0001
9 Electronics	13	11%	21	12%	19	35%	18.8868	.0001

ownership, product search, and perceptions of factors influencing the adoption of mobile shopping. We found significant differences across segments in the last three characteristics; as a result, we focus on reporting them in this section (for the others, please refer to previous sections).

First, there was a significant difference across segments in terms of ownership of smartphones, laptops, and tablets. Table 10 shows an increasing likelihood of owning different types of mobile devices and multiple devices from light to heavy users. Next, we consider information search behavior for 9 product categories. As in Table 10, 7 out of 9 Chi-square tests are statistically significant; exceptions are music and books. We observe an increasing trend in the likelihood of product search from light to heavy users, analogous to device ownership.

Finally, we show the differences across segments in important psychographic variables relating to the adoption of mobile shopping in Table 11. The two important predictors of behavioral intention—usefulness and ease of use—and other factors—hedonic motivation and facilitating conditions—were significantly different on many items across segments. Table 11 also illustrates the increasing trend on the scores of these items. Of interest, we did not observe a consistent trend in many items used to measured social influence and behavioral intentions. In fact, most of the significant differences came from the differences between moderate and heavy users; no significant differences were found between light and moderate users. This might suggest a nonlinear effect of our segments on these factors.

Implications of results

First, this study shows the popularity of mobile devices, especially smartphones, among educated young adults in Thailand. For example,

Table 11. Psychographic variables by segment.

	Item (measured on a 1–5 scale)	Segment: Light users	Moderate users	Heavy users	Analysis of variance: *F*	*p* value
PE1	I find mobile shopping useful	3.55	3.77	4.02	8.0937	.0004
PE2	Mobile shopping helps me save time	3.77	4.07	4.33	11.8567	<.0001
PE3	Mobile shopping increases my chances of getting special offers (e.g., discounts) and lower prices	3.41	3.47	3.89	6.8264	.0012
PE4	Mobile shopping is a convenient way to shop	3.68	3.87	4.11	6.3846	.0019
PE6	I find online product reviews useful	3.51	3.57	3.89	4.0059	.0191
EE1	Learning how to shop on mobile devices is easy for me	3.68	3.81	4.06	4.0270	.0187
EE3	It is easy for me to become skillful at mobile shopping	3.35	3.49	3.70	3.5267	.0305
HM1	Mobile shopping is fun	3.38	3.52	3.70	3.3848	.0350
HM2	Mobile shopping is enjoyable	3.47	3.53	3.78	2.8506	.0592
FC1	I have an Internet-enabled mobile device to shop	3.70	3.93	4.24	7.9159	.0004
FC2	I have reliable access to the Internet to shop on my mobile device	3.67	3.79	4.06	4.6099	.0106
FC3	I have the resources to purchase products or services on a mobile device (e.g., credit card or other forms of mobile payment)	3.16	3.40	3.67	5.5491	.0043
FC4	I have the knowledge necessary to shop on mobile devices	3.52	3.61	3.85	2.9628	.0530
SI1	People who are important to me think I should use mobile devices for shopping	3.18	3.14	3.41	2.5582	.0789
SI2	My friends think I should use mobile devices for shopping	3.25	3.17	3.50	3.6746	.0264
SI3	My family members think I should use mobile devices for shopping	3.12	2.92	3.44	7.9978	.0004
BI1	I intend to shop using mobile devices in the future	3.38	3.38	3.72	3.7468	.0246
BI3	I intend to make a higher percentage of my purchases using mobile devices in the future	3.33	3.24	3.54	2.9418	.0541
BI4	I intend to use online product reviews more frequently in the future	3.39	3.33	3.63	3.0880	.0469
BI5	I will write product reviews to aid others	3.37	3.27	3.67	4.4658	.0122

Note. PE: performance expectancy; EE: effort expectancy; HM: hedonic motivation; FC: facilitating conditions; SI: social influence; BI: behavioral intention.

respondents in our sample owned at least one mobile device, with 95% smartphone ownership. This also confirms the consistency of this particular group of users around the world as potential mobile device shoppers (Ström, Vendel, and Bredican 2014); for example, 89% of our sample had some mobile purchase experience. Of interest, it appears from our results that female users may be a more appealing target (than males) due to their higher proportion of smartphone ownership, higher purchase experience, and higher propensity to search information for their purchases on a regular basis.

Second, regarding activities on mobile devices, the popularity of social networking and general information search among these young adults has implications for marketers who desire to reach these users in Thailand. Of course, popular networking sites and search engines may vary across countries; for example, Facebook and Google (via google.co.th) are most common for Thai Internet users (gs.statcounter.com). In fact, Thailand is expected to be in the top 10 worldwide in terms of social media usage and consumer adoption growth in 2017 (Fredrickson 2017); this is not only an excellent channel to communicate to users but an accessible source of consumer information and preferences. Recent studies about commercial activities on social media in Thailand have further articulated the driving forces of this trend (Leeraphong and Papasratorn 2018) as well as the purchasing processes and business models being used (Sukrat, Mahatanankoon, and Papasratorn 2018). Next, while checking email was not often completed on mobile devices (ranked 8 in Table 5), we found that the likelihood of engaging in this activity varied significantly across groups with distinct purchase experience and the number of devices owned. This would allow marketers to target certain groups with a high propensity to check email on mobile devices. Because email marketing is highly profitable and widely used by marketers, we believe that this could be a potential tool to encourage purchase behaviors with the support of a suitable decision support system. For example, Zhang, Kumar, and Cosguner (2017) demonstrated how the number of emails sent affected the retailer's profitability. Last, single-device owners tended to be less active on certain activities, especially watching videos (with a decrease from 81% to 57%, see Table 6). Given that 92% of single-device owners had only a smartphone, this result may reflect the limitation of a smartphone in terms of screen size and processing capacity. It follows that marketers need to reconsider using videos to engage smartphone users; they could either reduce video usage or shorten the content.

Third, search behavior on mobile devices tended to be diverse across a wide range of product categories. This may partly reflect the differences in gender-specific tendencies. More important, we found other ambiguous differences in searching across many product categories (see Table 8). According to Shankar et al. (2016), there are two main drivers of mobile search—convenience and savings—however, the context that activates specific searches may provide more insights for marketers (Grewal et al. 2016). Our results with respect to product search indicate a greater need to understand contextual factors (e.g., location, weather, social, device, screen size) that trigger searches in specific product categories. For example, we showed that there was a decrease in the likelihood of searching electronics, travel services (e.g., airline ticket, hotel, and tour/vacation packages booking), books, movies, and transportation services (e.g., taxi, bus, and subway) with single-device ownership (primarily smartphone ownership). This may be because (1) the smaller screen sizes of smartphones increased search costs in these five product categories; (2) the lack of a second mobile device (while watching on the first one) restricted the propensity to search; or (3) the lack of reliable access to the Internet prevented mobile search for smartphone owners[1] or for other unknown reasons.

Finally, we identified three user segments among young adults based on their activities on mobile devices: light users (33% of the sample), moderate users (51%), and heavy users (16%). These segments varied significantly with respect to the variety of activities that they engaged in on a regular basis. Further, their profiles showed their differences on several other aspects. First, given the relatively high price of mobile devices in Thailand,[2] the measures of device ownership, especially multi-device ownership, could be an indicator of socioeconomic status. Plus, the increased likelihood of product search in all listed categories as well as regular search for purchase from light to moderate to heavy users (see Tables 9 and 10) provides strong support for the potential difference in socioeconomic status of the three identified segments. Specifically, heavy users may have the highest status, followed by moderate and light users. Second, the significant differences on many psychographic variables (from the information technology acceptance literature) show the relevance of our segmentation to the adoption of mobile shopping. Third, the pattern from Table 11 seems to indicate a non-linear effect of our segmentation on the adoption process; in other words, while heavy users tended to differ from the other two segments, the differences between light and moderate were quite subtle. Last, although smallest in group size, heavy users might be a good segment to target for marketers who want to increase mobile shopping for their products because of the high tendency for acceptance and the potential purchasing power of this particular segment (suggested from their high socioeconomic status).

Conclusions

In this article, we have attempted to provide a general understanding of mobile shopping behaviors of young adults in Thailand. Our findings yield important implications for marketers who are interested in reaching this growing market on mobile devices. Marketing a specific product category may require further research to better refine our results. For example, although we uncovered three mobile device user segments among young adults, how to market a specific product to these segments requires further understanding of the consumer path to purchase and best industry practices. As noted in Conick (2017), empowered by the flexibility of mobile devices such as smartphones, consumers are subconsciously or intentionally changing how they behave, what they value, and how they make shopping decisions. We hope our endeavors here will spark more efforts on researching emerging segments and markets.

Notes

1. Using analysis of variance on an item used to measure facilitating conditions, we showed that there was a lower perceived reliability of Internet access among single-device owners relative to multi-device owners ($F = 6.742$, $p = 0.0098$).
2. According to the World Fact Book from the Central Intelligence Agency (USA), Thailand's GDP per capita (PPP) was estimated at \$16,900 in 2016 (compared to \$57,400 in the US).

References

Blaise, R., M. Halloran, and M. Muchnick. 2018. Mobile commerce competitive advantage: A quantitative study of variables that predict m-commerce purchase intentions. *Journal of Internet Commerce*: 17 (2):96–114.

Conick, H. 2017. It's the end of retail as we know it: How can marketers adapt? *Marketing News*, September. Retrieved from: https://www.ama.org/publications/MarketingNews/Pages/end-retail-as-we-know-it-how-can-marketers-adapt.aspx.

Childers, T. L., C. L. Carr, J. Peck, and S. Carson. 2001. Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of Retailing* 77 (4):511–535. doi:10.1016/S0022-4359(01)00056-2

Davis, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13 (3):319–340. doi:10.2307/249008

Davis, F. D. 1993. User acceptance of information technology: System characteristics, user perceptions and behavioral impacts. *International Journal of Man-Machine Studies* 38 (3):475–1003. doi:10.1006/imms.1993.1022

Davis, F. D., R. P. Bagozzi, and P. R. Warshaw. 1989. User acceptance of computer technology: A comparison of two theoretical models. *Management Science* 35 (8):982–1003. doi:10.1287/mnsc.35.8.982

eMarketer 2016. Smartphone usage metrics in select countries in Southeast Asia, Q2 2015. Retrieved from https://www.emarketer.com/Chart/Smartphone-Usage-Metrics-Select-Countries-Southeast-Asia-Q2-2015/185834.

eMarketer 2017. Lazada dominates ecommerce activity in Southeast Asia – for now. Retrieved from https://www.emarketer.com/Article/Lazada-Dominates-Ecommerce-Activity-Southeast-AsiaFor-Now/1015360.

Fredrickson, T. 2017. Thailand in social media world's top 10. Bangkok Post. Retrieved from https://www.bangkokpost.com/learning/advanced/1255403/thailand-in-social-media-worlds-top-10.

Grewal, D., Y. Bart, M. Spann, and P. P. Zubcsek. 2016. Mobile advertising: a framework and research agenda. *Journal of Interactive Marketing* 34:3–14. doi:10.1016/j.intmar.2016.03.003

Kijsanayotin, B., S. Pannarunothai, and S. M. Speedie. 2009. Factors influencing health information technology adoption in thailand's community health centers: Applying the UTAUT model. *International Journal of Medical Informatics* 78 (6):404–416. doi:10.1016/j.ijmedinf.2008.12.005

King, W. R., and J. He. 2006. A Meta-analysis of the technology acceptance model. *Information & Management* 43 (6):740–755. doi:10.1016/j.im.2006.05.003

Krairit, D. 2018. The new face of internet user typology: The case of Thailand. *Journal of Theoretical and Applied Electronic Commerce Research* 13 (2):58–79. doi:10.4067/S0718-18762018000200106

Lee, M. K., and E. Turban. 2001. A trust model for consumer internet shopping. *International Journal of Electronic Commerce* 6 (1):75–91. doi:10.1080/10864415. 2001.11044227

Leeraphong, A., and B. Papasratorn. 2018. S-commerce transactions and business models in southeast asia: A case study in Thailand. *KnE Social Sciences* 3 (1):65–81. doi:10.18502/kss.v3i1.1397

Linzer, D. A., and J. B. Lewis. 2011. poLCA: An R package for polytomous variable latent class analysis. *Journal of Statistical Software* 42 (10):1–29.

Mayer, R. C., J. H. Davis, and F. D. Schoorman. 1995. An integrative model of organizational trust. *Academy of Management Review* 20 (3):709–734. doi:10.5465/amr.1995.9508080335

Maloney, D. 2017. Thailand 4.0. *DC Velocity,* September. Retrieved from http://www.dcvelocity.com/articles/20170912-thailand-40/.

Shankar, V., and S. Balasubramanian. 2009. Mobile marketing: A synthesis and prognosis. *Journal of Interactive Marketing* 23 (2):118–129. doi:10.1016/j.intmar.2009.02.002

Shankar, V., A. Venkatesh, C. Hofacker, and P. Naik. 2010. Mobile marketing in the retailing environment: Current insights and future research avenues. *Journal of Interactive Marketing* 24 (2):111–120. doi:10.1016/j.intmar.2010.02.006

Shankar, V., M. Kleijnen, S. Ramanathan, R. Rizley, S. Holland, and S. Morrissey. 2016. Mobile shopper marketing: Key issues, current insights, and future research avenues. *Journal of Interactive Marketing* 34:37–48. doi:10.1016/j.intmar.2016.03.002

Ström, R., M. Vendel, and J. Bredican. 2014. Mobile marketing: a literature review on its value for consumers and retailers. *Journal of Retailing and Consumer Services* 21 (6):1001–1012. doi:10.1016/j.jretconser.2013.12.003

Sukrat, S., P. Mahatanankoon, and B. Papasratorn. 2018. The driving forces of C2C social commerce in Thailand: A developing framework. *KnE Social Sciences* 3 (1):108–118. doi:10.18502/kss.v3i1.1400

Venkatesh, V., and F. D. Davis. 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science* 46 (2):186–204. doi:10.1287/mnsc.46.2.186.11926

Venkatesh, V., M. G. Morris, G. B. Davis, and F. D. Davis. 2003. User acceptance of information technology: Toward a unified view. *MIS Quarterly* 27 (3):425–478.

Venkatesh, V., J. Y. Thong, and X. Xu. 2012. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly* 36 (1):157–178.

Wang, R. J. H., E. C. Malthouse, and L. Krishnamurthi. 2015. On the go: How mobile shopping affects customer purchase behavior. *Journal of Retailing* 91 (2):217–234. doi:10.1016/j.jretai.2015.01.002

Williams, M. D., N. P. Rana, and Y. K. Dwivedi. 2015. The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management* 28 (3):443–488. doi:10.1108/JEIM-09-2014-0088

Zhang, X., V. Kumar, and K. Cosguner. 2017. Dynamically managing a profitable email marketing program. *Journal of Marketing Research* 54 (6):851–866.