Received 18 November 2011
Revised 9 January 2012
29 May 2012
27 September 2012
11 November 2012
17 December 2012
Accepted 20 December 2012

Urban and rural differences

Multilevel latent class analysis of online activities and e-payment behavior patterns

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Abstract

Purpose – The purpose of this article is to investigate urban and rural differences for online activities and e-payment behavior patterns.

Design/methodology/approach – This study applied the MLCA model to investigate Internet usage patterns from 11 online applications among 10,909 Taiwan residents in 25 different regions.

Findings – The results showed that online behavior patterns exhibited regional differences, as the regional segments affected the individual segments of different use patterns. For instance, the urban area comprised a higher proportion of members who were accustomed to internet applications and skilled in online shopping by using a credit card. The rural area made up a higher proportion of members who only occasionally used online services. Moreover, rural region residents used other payment methods (excluding credit cards) more often than urban region residents. As expected, users' personal characteristics also dictated the online behavior pattern. For instance, people with higher-level income spent relatively more money for online shopping and often used various internet applications than others.

Practical implications – The findings herein should help Internet service providers form an applicable guideline for developing service strategies of higher service satisfaction regarding products and users' needs.

Originality/value – This study implemented a multilevel latent class model to investigate online behavior patterns that exhibited urban and rural differences, with the goal of providing service providers an understanding and mastery of their target users.

Keywords Online payment, Online behaviour pattern, Urban and rural differences, Multilevel latent class analysis, Consumer behaviour, Rural regions, Urban regions, Taiwan

Paper type Research paper

Introduction

The internet is influencing people's daily lives more so than it did in the past. People's daily activities have gradually shifted from concrete circumstances to virtual environments. The shopping and payment environments have also changed from physical stores into online ones. More and more people are contributing to the

1066-2243
DOI 10.1108/10662241311313321

generation of online applications, such as e-news, information search, purchases, and banking transaction (Frost *et al.*, 2010; Huang, 2012). The internet is popularly celebrated as transforming all sectors of everyday life from the economy to civic society (Selwyn *et al.*, 2005). Such changes have motivated internet service providers to value users' needs and their internet usage behaviors more so than before. Data regarding users' online behavior are needed to help service providers define their online service strategies for web site design, online advertising, market segmentation, product variety, inventory holding, and distribution (Tamimi *et al.*, 2003; Ha and Stoel, 2012). For service providers, understanding and mastering users' needs through their behaviors in the internet have genuinely become competing elements to take into account. Forecasts are more likely to be reliable if they are based on consumers' online behaviors (Ha and Stoel, 2012; Wu *et al.*, 2012). If a marketer on the internet is able to identify potential early adopters and understand their personalities, then along with appropriate incentives it can facilitate the adoption process (Citrin *et al.*, 2000; Tamimi *et al.*, 2003). For many e-commerce studies, urban and rural differences in e-payment study were rare in the past. Travica (2002) compared e-payment activities between a developing country and a fully developed one (Costa Rica vs North America). One of the major findings was that technological, economic, and cultural specificities are likely to influence the acceptance of e-payment.

Understanding online behaviors may help increase service satisfaction between products and users' needs. This study looked at online behavior patterns in particular issues related to online payment and security. Users' behaviors may not be independent when the data structure includes citizens living in the same city, employees of the same company, or students from the same school. In other words, since users of the same region share similar backgrounds, environment may be one of the influential factors regarding internet behavior. The purpose of this paper was mainly to investigate urban and rural differences for online activities and e-payment behavior patterns. The investigation herein examined the extent to which there were cross-regional vs regional-specific user segments defined by behavior patterns and whether groups of regions existed that were homogenous in their user segment structure. In particular, the relative sizes of cross-regional user segments determined region segmentation. The simultaneous approach ensured that both regional-specific and cross-regional user segments were accommodated. This paper investigated the usage behaviors through 11 items of categorical variables on online behavior among 16,133 users in 25 regions of Taiwan. This study implemented a multilevel latent class model to investigate online behavior patterns that exhibited urban and rural differences, with the goal of providing service providers an understanding and mastery of their target users.

The research questions of this study are:

RQ1. Do online behaviors exhibit certain identifiable patterns?

RQ2. Do online behavior patterns exhibit urban and rural differences?

RQ3. What kind of special or interesting online behavior pattern differences exist?

Literature review

The effect from location and personal characteristics

The digital divide between rural and urban areas still influences how telecommunications and other advanced technologies are used (Donnermeyer and

Hollifield, 2003). Socio-economic factors affect the usage of information and communications technology and also form urban and rural differences (Cullen, 2003). The diffusion of the internet occurs at the intersection of both international and within-country differences in socio-economics (Chen and Wellman, 2004). Accordingly, socio-economic status is an important predictor of how people are incorporating the web into their everyday lives (Hargittai, 2010). The opportunities and material circumstances impact people's extent or degree of participation and engagement in using the internet (Selwyn *et al.*, 2005; Li *et al.*, 2012). Users who have more connection points to access the internet are more likely to use it for beneficial purposes, including seeking general information, researching products, and purchasing products (Hassani, 2006; Chiang, 2012). Divergent regions have different infrastructures, economies, and populations, leading to environmental diversifications of location (Mills and Whitacre, 2003). Hence, this also affects the divergence among citizens' internet usage patterns (Wilson *et al.*, 2003; Yeh *et al.*, 2012). Users in the same region have the same background environment, and therefore when discussing online behaviors across different region, like rural vs urban, researchers should take account the environments, so that they can accurately compare the online behaviors of users from different regions. This paper has herein referenced and analyzed the findings from the scholars mentioned above and the regional differences.

In addition to location, other factors that influence online behaviors, such as users' social status, age, income, and gender, are also major concerns (Teo, 2001; Agarwal *et al.*, 2009; Wei *et al.*, 2011). For example, variables covering personal characteristics, use, and expertise play a role in accounting for variations in the breadth and depth of internet usage, among which demographic variables such as gender, income, and age have significant influences (Wasserman and Richmond-Abbott, 2005; Livingstone and Helsper, 2007; Agarwal *et al.*, 2009). Hargittai and Hinnant (2008) present that online usage pattern differences are very divergent among internet users. People with less economic pressure are more likely to engage in impulse buying behavior and female conformity behaviors are higher than that for males (Hernández *et al.*, 2011). Shoppers' age, occupations, income, and online shopping expenses are also influential (Ho and Oh, 2009; Hernández *et al.*, 2011). Korupp and Szydlik (2005) discover that social capital such as age, gender, and residence are important in explaining private internet use. The types of internet content may attract users who seek to satisfy certain motivations more broadly, potentially because of their social situation (Shah *et al.*, 2001). Maldifassi and Canessa (2009) indicate that the main factor influencing IT use and perception is social class: the higher a user's social class, the more positive their perception of IT with a higher level of usage frequency. Teo and Lim (2000) prove that different genders and age levels have a significant impact on online use patterns. Personal characteristics affect internet use, such as duration of internet usage access time, motivation for using the internet, internet skill acquisition, and evaluation of internet information content (Akporido, 2005). This study referenced the findings from the scholars mentioned above and included some personal characteristic variables such as age, income, gender, and online shopping expenses into the research model to analyze how these personal characteristic variables influenced the pattern of online behavior.

Online activities and e-payment behavior

Internet applications and services enrich peoples' lives. Howard *et al.* (2001) indicate that internet usage patterns in the US encompass communication, fun, information utility, major life activities, and transactions. Colley and Maltby (2008) reveal that the most common internet applications are job enhancement, communicating with friends, browsing news, acquiring general information, trading, banking, and shopping. Stepanikova *et al.* (2010) stated that internet usage is motivated by communication (i.e. e-mail) and information acquisition (i.e. browsing news). People usually use the internet for e-mail, online newspapers, searching for job information, ravel booking, e-shopping, and electronic banking (Bonfadelli, 2002; Zhu and Chen, 2012).

The internet industry currently faces the challenge of determining how to offer the "right" product variety to the target market. The most important aspect for a web store is information with respect to product functions and payment methods (Luo *et al.*, 2011; Sabiote *et al.*, 2012). Internet banking services are gaining popularity, but some people worry about security issues and lack trust toward the internet banking services (San Martín *et al.*, 2011). In the online environment, e-payment is a process to complete the transaction. E-payment services are web-based user-interfaces that allow customers to remotely access and manage their bank accounts or transactions (Lim, 2008; Zhou, 2011). Hence, e-payment has become one of the most important factors for successful business and financial services (Kim *et al.*, 2010; Zhou, 2011). E-payment has several important characteristics, including security, scalability, reliability, anonymity, acceptability, privacy, convenience, and efficiency (Kim *et al.*, 2010; Benlian *et al.*, 2012).

Hargittai and Hinnant (2008) suggest that user attributes such as online skill an important mediating factor in the types of people's online activities. User interactions (such as functional performance, perceived control skill, and perceived trust) with a retail web site can affect the purchase behavior (Rose *et al.*, 2011; Bordonaba-Juste *et al.*, 2012). Doubts about information security and privacy for online shopping can strongly influence the consumer's purchase intention (Ho and Oh, 2009; Hsiao, 2011). In the virtualization service environment, payment methods, security, and copyright are new issues that have not yet been discussed.

Based on previous studies, this study categorized several online behaviors that frequently occurred and chose 11 of them to analyze. These 11 behaviors encompassed: using the internet for work, sending/receiving mail, browsing news, searching for public notices, four types of online shopping use payment methods (such as credit card, e-banking, cash, and others), online security sense, online security ability, and intellectual property rights (IPR) sense.

Investigating user behavior patterns

Some scholars indicate that understanding user behaviors on the internet helps in products' research and development, together with their sales (Lohse *et al.*, 2000; Wang and Li, 2012). Scholars show differences among time, frequency, and range of internet usage (Katz *et al.*, 2001; Selwyn *et al.*, 2005). Hernández *et al.* (2011) present that due to the diversity in individual usage behaviors, cognitive needs, and personality, a further research of methods on clustering users may be quite interesting and helpful. Some studies suggest sorting online use pattern by users' age (Shah *et al.*, 2001), while others explore the length of experience, access time, and frequency of online use patterns (Howard *et al.*, 2001; Donnermeyer and Hollifield, 2003; Akporido, 2005).

Another way to examine which types of individuals conduct what pattern of online activities or motives is to explore user typologies. For example, researchers use factor analysis to investigate the online motivated patterns among various users (Teo, 2001; Hernández *et al.*, 2011). In the social sciences, many studies investigate the construct relationship when both categorical outcomes and predictor variables are latent (Cooil *et al.*, 2007; Fuller and Dennis, 2009; Fischer and Albers, 2010). Categorical data analysis is very useful in the analysis of sociological data (Goodman, 2007). The introduction of the latent class procedures may direct researchers' attention to developing better in terms of helping recognize the potential unobserved heterogeneity in organizational phenomena and processes (Wang and Hanges, 2011). For an attitude or classification survey, researchers are generally more concerned about the potential groups of samples and the latent class model since these groups can provide a better means to categorize data. With an attitude or classification survey, it is more appropriate to use latent class analysis (Bijmolt *et al.*, 2004; Van Horn *et al.*, 2008). In online behavior studies, users' behaviors usually present categorical outcomes, a latent usage pattern, and region influence. Although the length of experience and frequency of online use can help predict which activities people engage online, the patterns of online behavior have also been proved to be a significant predictor. This study tested such a particular relationship of types of online usages. This study took the methodology from previous scholars and applied multilevel latent class analysis (MLCA) to investigate user behavior patterns based on multilevel data structures (Bijmolt *et al.*, 2004; Van Horn *et al.*, 2008; Henry and Muthén, 2010).

Methodology

This study applied MLCA to attain regional segmentation (T; level 2) and cross-region user segmentation (S; level 1). MLCA is a model-based tool for both regular user segmentation and regional segmentation (Vermunt, 2003; Bijmolt *et al.*, 2004; Van Horn *et al.*, 2008; Henry and Muthén, 2010). Maximum likelihood estimates the parameters of the MLCA model, in which an adapted version of the expectation-maximization algorithm achieves the maximization of the likelihood function (Vermunt, 2003; Bijmolt *et al.*, 2004). Estimations are obtained for fixed numbers of regional segments and user segments. Estimating the MLCA for different values of T (level 2) and S (level 1) and examining the relative fit of alternative model specifications, e.g., by using the minimum BIC rule, can determine the appropriate values for these numbers (Vermunt, 2003; Van Horn *et al.*, 2008; Henry and Muthén, 2010). This study used LatentGold V.4.5 to analyze the data. In addition, this study used SPSS v12.0 to collate data descriptive statistics and the contingent table.

Sample

In 2009 Taiwan's average percentage of household internet access was 78.1 percent, and average daily time spent on the internet was 2.95 hours (Research, Development and Evaluation Commission (RDEC), 2009). Taiwan's internet prevalence equals the standard of developed countries, such as the USA (77.3 percent), Austria (74.8 percent), France (68.9 percent), Germany (79.1 percent), Japan (78.2 percent), and Singapore (77.8 percent) (Miniwatts Marketing Group, 2010). Therefore, the surveyed data of online behavior that Taiwanese residents possessed could be a reference to some extent and also can offer a good source for service providers to work on internet products and marketing services. The collected data for all analyses adopted the digital divide survey conducted by the RDEC, which evaluated the situational status of the current digital divide and internet usage behaviors in Taiwan. The method of survey was through computer and telephone interviews from July to August in 2009. The investigation took random population sampling interviews on a segmented population of interviewees from age 12 and above in 25 counties and cities. The selection of random population samples by telephone interviewing of study subjects was chosen in which household telephone numbers for its last two digits (per regional code) were all included as sample targets. Taken into consideration several factors such as age, ability to act independently, purchasing power, and the education system on computer usage in Taiwan, this survey focusses on users 12 years old and above (the legal age for children to stay at home alone is 12 years old. On the other hand, the age when individuals are taught computer usage skills in school is ten years old and above in Taiwan.). Taiwan government policy indicates that adolescence have fundamental computer education in junior high school. In general, they are familiar with web browsing and most have experienced e-shopping. The survey collected 16,133 valid random samples with a response rate of 66.4 percent, and the sampling errors did not exceeded ± 4 percent. This annual survey included three parts: information and communications technology environment, skills to use the internet, and online behaviors. This study used 11 items of categorical variables about online behavior as a research dataset. The data were in exclusion of missing values for the 10,909 valid samples. To achieve valid inferences in the MLCA, this study weighted each observation by a sample size according to the population by gender, age, and each region.

This study herein has referenced the findings from the scholars mentioned above and chose those frequently occurred online behaviors which are related to work need (such as using the internet for work, sending/receiving mail, browsing news, searching for public notices), online shopping use payment methods (such as credit card, e-banking, cash, and others), and security judgment (such as online security sense, online security ability, and IPR sense) to analyze. The method herein used 11 categorical indicators to inform latent class membership: using the internet for work (1 = yes, 0 = no), sending/receiving mail (1 = yes, 0 = no), browsing news (1 = yes, 0 = no), searching for public notices (1 = yes, 0 = no), online shopping using a credit card (1 = yes, 0 = no), online shopping using e-banking (1 = yes, 0 = no), online shopping using cash (1 = yes, 0 = no), online shopping using other payment methods (such as micropayment and convenience store payment) (1 = yes, 0 = no), online security sense (such as refusal to open an unknown e-mail) (1 = yes, 0 = no), online security ability (such as changing a password) (1 = yes, 0 = no), and IPR sense (when one gets data from the internet for personal use that still need to consider copyright issues) (1 = yes, 0 = no). Although the frequency of usage can influence internet behavior, yet from interviews with past individuals it can be concluded that most participants are merely willing to answer a simple "yes" or "no" question. There are only a few minorities of participants that can differentiate without difficulty the options "often use," "used before," and "never." Due to this phenomenon, our study has not included the frequency of internet usage. This study followed the questionnaire deign of Henry and Muthén (2010). The online behaviors of these participants are categorized as (1 = yes) and (0 = no) as categorical outcomes. This paper observed latent classes of online behavior among 10,909 Taiwan residents who lived in one of 25 different regions. This data structure represented a nested or multilevel design in which individuals showed a level 1 (S) of the hierarchy and regions represented level 2 (T). This study took both individual and contextual level predictors of online behaviors' typologies. Descriptive statistics for the internet use sample filled up Table I.

To assess the significance of the city/county effects, this study employed the likelihood ratio χ^2 test for online behaviors. The middle part of Table I made up the city or county variables that significantly affected some of the (seven out of 11) online behaviors: using internet for work, sending/receiving mail, browsing news, searching

Table I. Descriptive statistics for the online behavior sample

Region	Sample size	Average weight	Online behavior (sample proportion): Using the internet for work	Sending/receiving mail	Browsing news	Searching for public notices	Online shopping using a payment method: (Credit card)	(e-banking)	(Cash)	(Other)	Online security sense	Online security ability	IPR sense
Taipei City	813	2.28	32.0	92.0	86.7	90.3	23.7	21.9	13.1	15.6	75.9	76.8	51.5
Taipei County	818	3.32	25.0	90.3	81.5	87.3	18.1	22.7	11.8	13.7	73.0	72.5	48.7
Keelung City	601	0.46	24.9	91.5	80.4	85.2	17.9	21.9	15.8	15.4	71.4	75.1	54.2
Yilan County	603	0.53	19.9	94.4	80.2	81.3	10.9	19.3	13.7	12.5	76.3	71.6	52.3
Taoyuan County	812	1.65	27.2	89.7	81.0	86.2	15.9	20.3	16.7	12.3	74.3	71.9	50.8
Hsinchu County	608	0.56	27.5	91.0	81.1	83.3	12.7	22.2	12.4	10.9	73.4	78.1	49.8
Hsinchu City	607	0.45	30.3	92.8	82.2	86.1	20.4	26.3	16.5	11.3	72.1	79.4	49.0
Miaoli County	603	0.64	22.5	92.6	83.2	82.4	10.6	20.2	15.2	12.9	74.6	69.5	53.1
Taichung County	602	1.80	22.6	89.4	77.5	82.6	23.7	18.9	13.0	12.4	70.8	72.7	49.0
Taichung City	800	0.93	30.7	92.7	80.5	90.1	18.7	24.0	14.3	14.3	76.1	75.0	53.1
Changhua County	600	1.53	20.3	89.3	76.6	84.5	10.3	17.4	14.4	12.6	73.1	66.7	48.9
Nantou County	605	0.61	18.9	92.7	77.7	82.3	8.1	18.6	13.0	12.4	72.7	71.4	51.4
Yunlin County	604	0.83	16.0	90.9	75.5	84.5	9.4	13.6	10.6	10.8	76.2	70.6	54.0
Chiayi County	602	0.64	14.2	86.7	74.9	82.5	7.2	11.9	11.7	9.8	69.2	66.4	53.6
Chiayi City	606	0.32	21.8	89.3	82.4	86.3	12.4	19.6	14.5	11.4	68.9	74.2	57.3
Tainan County	600	1.32	17.9	86.2	79.1	83.2	8.7	17.4	11.2	11.1	71.3	67.1	55.6
Tainan City	603	0.88	21.8	91.8	78.5	87.3	13.0	19.4	10.9	11.9	73.7	71.4	52.1
Kaohsiung City	800	1.35	23.2	89.6	81.4	83.8	13.8	19.9	12.6	13.9	72.6	71.9	50.2
Kaohsiung County	605	1.44	17.1	88.9	78.4	82.9	11.1	18.1	11.8	10.8	71.1	72.1	54.1
Pingtung County	601	1.04	14.7	85.4	75.8	83.0	9.6	16.4	11.6	8.8	67.5	66.5	54.1

(*continued*)

Table I.

Region	Sample size	Average weight	Online behavior (sample proportion): Using the internet for work	Sending/receiving mail	Browsing news	Searching for public notices	Online shopping using a payment method: (Credit card)	(e-banking)	(Cash)	(Other)	Online security sense	Online security ability	IPR sense
Penghu County	608	0.11	18.5	91.7	82.9	83.3	9.2	17.2	12.5	12.3	71.4	74.3	51.4
Hualien County	606	0.40	24.4	88.7	80.4	84.8	13.3	22.8	17.8	15.4	73.4	72.2	53.8
Taitung County	605	0.27	21.7	89.4	79.8	88.5	13.7	23.5	17.4	15.5	76.0	71.2	51.9
Kinmen County	602	0.11	23.1	92.5	90.0	90.0	14.1	23.4	12.3	10.9	75.0	70.0	52.5
Leinchiang County	619	0.03	31.3	90.9	90.0	90.0	18.8	31.3	6.3	11.8	72.7	80.0	45.5
Total	16,133		23.6	90.2	80.6	85.8	14.7	20.1	13.1	12.8	73.2	72.3	51.3
Likelihood ratio χ^2 test			115.93**	44.12**	70.09**	68.38**	187.24**	29.52	46.95**	24.66	24.97	54.68**	21.17
Personal characteristics													
Age	14 and younger	15-20	21-30	31-40	41-50	51 and older			*Gender*	Female	Male		
%	4.80	9.60	18.20	18.42	18.65	30.33			%	49.84	50.16		
Income	Low	Middle	High	Uncertain	*Online shopping expenses (USD/year)*			<171	171-1,714		>1,714		Uncertain
%	29.76	26.75	8.26	35.20			%	22.33	12.494		1.39		63.78

Note: ***p*-value <0.01

for public notices, online shopping using a credit card, online shopping using cash, and online security ability, respectively. Table I showed that online behaviors likely exhibited several differences among cities and counties. This study took this result and used MLCA to further investigate whether regional differences existed within the online behavior patterns.

Model fit

In order to study the similarities and differences between the patterns of online behaviors from 11 internet applications among 10,909 users and 25 regions, this study applied the MLCA model described beforehand. This paper incorporated effects of four personal characteristic variables (age, income, gender, and online shopping expenses) by means of concomitant variables. The study obtained model estimates for alternative numbers of user segments ($S = 1$-5) and regional segments ($T = 1, 2$). Table II depicted model fit (in particular, the BIC value) for each combination of S and T. The optimal number of user segments applied the minimum BIC (Vermunt, 2003; Van Horn *et al.*, 2008; Henry and Muthén, 2010). The finding attained the overall minimum BIC at five user segments and two regional segments (BIC = 117,546), which this study identified as the most appropriate solution. The study also checked the reports' model fit through the result of the Wald test (Wald, 1943; Buse, 1982). The Wald value of the model for regional clusters (25 cities/counties in level 2; $T1 = 26.38$, p-value < 0.001; $T2 = 24.33$, p-value < 0.001) meant that the contextual level split into two segments (T) with a significant difference (Wald, 1943; Agresti, 2007). In addition, the individual level (level 1 has 11 online applications among 10,909 users) separated into five segments (S) and also showed a significant difference (all p-values < 0.001). Four personal characteristic (covariate) variables significantly affected the individual level: age (Wald = 589.69, $p < 0.001$), income (Wald = 299.52, $p < 0.001$), gender (Wald = 20.54, $p < 0.001$), and online shopping expenses (Wald = 1,026.52, $p < 0.001$). Therefore, this study divided the user level (S) into five segments and regional level (T) into two segments, which altogether induced the most appropriate solution.

Results

User and regional segmentation

Table III presented online activities and e-payment behaviors within each user segment. Within the table, the study acquired conditional probability for this

BIC Number of individual segments	Number of regional segments 1	2	3
1[a]	127,647	127,657	127,666
2	120,972	120,941	120,948
3	118,332	118,276	118,273
4	117,847	117,789	117,790
5	***117,627***	***<u>117,546</u>***	***117,554***
6	117,650	117,568	117,594
7	117,644	117,617	117,615

Notes: The lowest BIC within each row is in italic and within each column is in boldface. The lowest BIC overall is underlined. [a]If $S = 1$, then the number of regional segments (T) is also restricted to 1 by definition

Table II. Model fit (BIC) for alternative numbers of regions and user segments

Cluster size	S1 35%	S2 20%	S3 19%	S4 15%	S5 11%	Likelihood ratio chi-square test χ^2	p-value
	Individual segment						
Online behaviors	*Behaviors' probabilities*						
Using the internet for work	0.70	0.02	0.01	0.52	0.09	6,092.56	0.00
Sending/receiving mail	1.00	0.99	1.00	1.00	0.07	6,223.99	0.00
Browsing news	0.94	0.85	0.66	0.80	0.56	1,209.81	0.00
Searching for public notices	0.97	0.79	0.69	0.95	0.77	1,356.68	0.00
Online shopping using a credit card	0.52	0.08	0.00	0.04	0.04	4,230.76	0.00
Online shopping using e-banking	0.52	0.50	0.01	0.03	0.04	3,965.83	0.00
Online shopping using cash	0.31	0.36	0.01	0.01	0.07	2,037.95	0.00
Online shopping using other payment methods	0.27	0.44	0.01	0.01	0.04	2,406.20	0.00
Online security sense	0.82	0.79	0.82	0.83	0.00	3,292.30	0.00
Online security ability	0.88	0.80	0.67	0.68	0.19	2,090.36	0.00
IPR sense	0.47	0.52	0.59	0.53	0.47	79.03	0.00
Regional segments	*Relative sizes of individual segments*					196.66	0.00
T1 (72.65%)	0.34	0.21	0.19	0.15	0.11		
T2 (27.35%)	0.40	0.17	0.19	0.14	0.10		
Personal characteristic variables	*Relative sizes of individual segments*						
Age						7,444.60	0.00
14 and younger	0.00	0.16	0.71	0.00	0.12		
15-20	0.00	0.49	0.47	0.00	0.04		
21-30	0.41	0.32	0.13	0.10	0.04		
31-40	0.60	0.06	0.06	0.18	0.09		
41-50	0.43	0.06	0.06	0.27	0.19		
51 and older	0.25	0.09	0.13	0.30	0.24		
Income (household income per month)						2,392.94	0.00
Low (<US$1,714)	0.23	0.22	0.22	0.14	0.19		
Middle (US$1,714-2,742)	0.50	0.16	0.09	0.17	0.08		
High (>US$2,742)	0.66	0.08	0.04	0.18	0.04		
Uncertain (or refused to answer)	0.19	0.27	0.32	0.13	0.10		
Gender						87.78	0.00
Female	0.38	0.22	0.17	0.13	0.11		
Male	0.33	0.19	0.21	0.17	0.11		
Online shopping expenses per year						12,399.33	0.00
<US$171	0.47	0.49	0.00	0.00	0.03		
US$171-1,714	0.84	0.14	0.00	0.00	0.02		
More than US$1,714	0.91	0.06	0.00	0.00	0.03		
Uncertain	0.06	0.02	0.40	0.32	0.19		

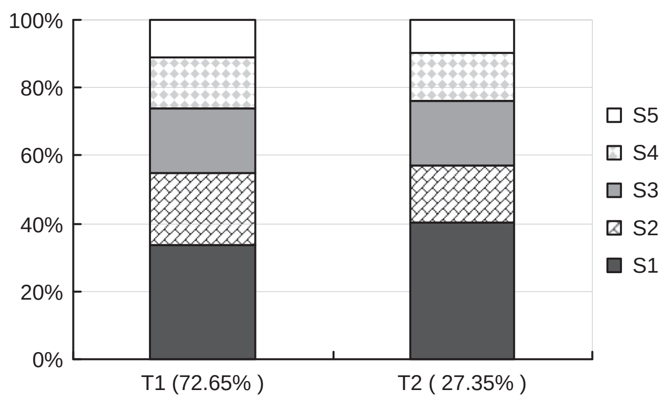
Table III. Model results: user segments and effects of personal characteristic variables

research target, which consisted of 11 users' online behaviors. At the individual level, this paper discovered that the application behavior patterns of the internet consisted of five segments (referred to as S1-S5), which showed distinctive usage patterns.

In the middle part of Table III, the results linked regional and user segments. Taiwan is divided into two regional segments (referred to as T1 and T2), where segment probabilities represented the relative sizes within a regional segment, and the population size of each group was 72.65 percent (T1) and 27.35 percent (T2), respectively. In order to deduce interpretation, this paper offered segment membership probability through the category of each regional segment, averaged across all categories of the other regional segments. For example, the rate of T2 in each user segment (S1-S5) was 40, 17, 19, 14, and 10 percent (total = 100 percent), respectively. Based on the individual level (five segments) and contextual level (two segments), this paper summarized the multi-contingency by a table of regional segments, user segments, and administrative regions of Taiwan (see Appendix). Regional segment 1 (T1) included relatively more rural areas, and most of the local governments focussed on agricultural or tourist development. This class represented the rural segment. Regional segment 2 (T2) included relatively higher concentrations and a more complete infrastructure. This class is made up of the urban segment. The findings from the regional segments of the user segment details are shown in Figure 1. This paper referenced the practice of Henry and Muthén (2010), showing that the two regional segments compositions vary. Regional segment 2 (T2) included relatively more knowledge segment (S1) whereas regional segment 1 (T1) included relatively higher concentrations of online shopping segment (S2).

Effect of personal characteristic variables

Users' online behaviors and thereby membership of user segments are often related to personal characteristic variables such as age, income, gender, and online shopping expenses. This paper assessed the effects of four personal characteristic variables: age, income, gender, and online shopping expenses. Ages included 14 and under, 15-20, 21-30, 31-40, 41-50, and above 51 for six categories. The income (household monthly income) included less than low (< US\$1,714), middle (US\$1,714-2,742), high (more than US\$2,742), and refused to answer, and this was contingent for four categories. The online shopping expenses per year included < US\$171, US\$171-1,714, more than US\$1,714, and refused to answer, and this was contingent for four categories. The lower part of Table III entailed the findings for the effects of personal characteristic variables. In order to deduce further interpretation, this paper referenced the practice by Bijmolt *et al.* (2004). This paper did not present logic parameters, but instead segmented membership probability per category of each personal



Notes: T1, rural region; T2, urban region; S1, knowledge segment; S2, online shopping segment; S3, protected segment; S4, social participation segment; S5, occasional segment

Figure 1. Multilevel latent class solution

characteristic variable, averaged across all categories of the other variables. For example, the rate of males in each user segment (S1-S5) was 33.1, 18.6, 21.0, 16.7, and 10.6 percent (total = 100 percent), respectively.

Full model estimated

To further assess the significance of the urban and rural differences, the middle part (right side) of Table III evidenced that the regional segment variables significantly affected individual segment (user segment) membership ($\chi^2 = 196.66$; df = 4; p-value < 0.001). These results showed that the online behavior patterns exhibited urban and rural differences. For instance, the urban area segment comprised a higher proportion of members who were familiar with using the internet. The rural area segment made up a higher proportion of members who unfamiliar with used the internet. These two regional segments of the composition were different.

This paper modeled the probability that a user belonged to a particular segment depending upon his/her personal characteristics and on regional segmented membership. To assess the significance of the personal characteristic effects, the method herein employed the likelihood ratio test for nested models. In the right side of Table III all four personal characteristic variables significantly affected user segment membership: age ($\chi^2 = 744.60$; df = 20; p-value < 0.001), income ($\chi^2 = 2,392.94$; df = 12; p-value < 0.001), gender ($\chi^2 = 87.78$; df = 4; p-value < 0.001), and online shopping expenses ($\chi^2 = 12,399.33$; df = 12; p-value < 0.001). Users' personal characteristics dictated the individual segments. Age, income, and online shopping expenses had a large influence on the user segment probabilities. For instance, younger people were familiar with various online services, as they had more online security capability than others. Older people were less likely to use online payment applications. People with higher level income spent relatively more for online shopping than others. Of the users' personal characteristics included in this study, gender had the smallest impact, as shown by the χ^2 test values and the differences between the segment membership's probabilities. Generally speaking, males had a relatively high sense of online security, while females had a comparative concern for public service.

Discussion

This study took the contextual effect influenced by areas and their personal characteristics variation into account for analysis. The conditional probabilities of each of the 11 types of usage behavior within each individual segment (S1-S5, level 1) made up Table III. By considering some personal characteristic variables such as age, income, gender, and online shopping expenses, this paper divided user segmentation at the individual level into five groups and regional segmentation at the contextual level into two clusters. This gained striking and significant results. The clusters identified in this research (S1-S5 and T1-T2) effectively partitioned the online behavior patterns among 10,909 users and took into account the potential classification of the usage model behind the personal characteristic variables.

Online users' behavior pattern

User segmentation in each model of users' online behaviors turned out to be different. Figure 1 and Table III summarized the detailed classification of users' online behaviors.

Considering the contextual level (regional) and personal characteristic variables, this study analyzed five patterns of users' online behaviors (user segments S1-S5):

- S1: This segment consisted of 35 percent of the total samples, chiefly composed of those aged 21-50 who had a relatively high level of income and online shopping expenses. This group was knowledgeable on various internet applications, such as using internet for work (70 percent), sending/receiving mail (100 percent), browsing news (94 percent), and searching for public notices (97 percent). Within this group, more than 50 percent experienced online shopping using a credit card or e-banking and their online security sense was up to 88 percent – these were the highest conditional probabilities of all segments. Interestingly, only 47 percent of them had any sense of IPR. This was the lowest conditional probability of all segments. This group had more women than men. Their contextual level (regional segment) had a maximum number in the urban segment. This group entailed the knowledge segment.
- S2: This segment consisted of 20 percent of the total samples, chiefly composed of those aged 15-30 who had a middle level of income and online shopping expenses of about US$171-1,714. They were familiar with sending/receiving mail (99 percent), browsing news (85 percent), and searching for public notices (79 percent). They had more sense of IPR (52 percent), higher online security ability (80 percent), and completed online shopping by using e-banking (50 percent) or cash (36 percent). This group had the highest conditional probability of online shopping using other payment methods (44 percent) such as micropayment and convenience store payment. They had lower proportions to use internet for work (2 percent), and use a credit card for online shopping (8 percent). Their contextual level (regional segment) had a maximum number in the rural segment. This group became known as the online shopping segment.
- S3: This segment consisted of 19 percent of the total samples, chiefly composed of teenagers who had a low level of income. Therefore, the users in this segment lack online shopping experience due to the level of income and restriction of online shopping expense. Most of them were skilled in sending/receiving mail (100 percent) and online security ability (67 percent). They had more sense of online security (82 percent) and the highest conditional probability of IPR sense (59 percent). They did not relatively care about public notices (69 percent) and less experienced online shopping (1 percent). This was the lowest conditional probability of all segments. Their contextual level resided evenly in each regional segment. This group took the title of the protected segment.
- S4: This segment consisted of 15 percent of the total samples, chiefly composed of middle-aged people. They were familiar with internet information search and social participation, such as using the internet for work (52 percent), sending/receiving mail (100 percent), browsing news (80 percent), and searching for public notices (95 percent), respectively. More than 83 percent of them had a sense of online security. This was the highest conditional probability of all segments. Their online security ability was relatively high (68 percent), whereas their IPR sense (53 percent) was also significantly prominent. They had lower proportions to conduct online shopping (1-4 percent). Their contextual level (regional segment) had a maximum number in the rural segment. This group filled up the social participation segment.

- S5: This segment consisted of 11 percent of the total samples, chiefly composed of those aged older than 51. Those people had a relatively low level of income and various online shopping expenses. They used internet applications relatively less, such as browsing news (56 percent) and searching for public notices (77 percent). They rarely used the internet for work (9 percent) and seldom took action for sending/receiving mail (7 percent). Only 19 percent of them had online security ability, nor online security sense, and <7 percent of them had experienced online shopping. Their contextual level (regional segment) had a maximum number in the rural segment. This group fitted the occasional segment.

These five user segments showed distinctive online behavior patterns. The knowledge segment's members were knowledgeable on various internet applications, but were also more ignorant of IPR than others. Most of the knowledgeable users spent relatively more for online shopping than others, and web sites could offer these users discounts of customization to attract their purchases. Although the online shopping segment group did not have high incomes, these people were skillful in various online payment methods (except credit cards). Due to these characteristics, they have a high possibility of becoming potential online customers in the future. Should service designer target this group, then it could use pre-introduction or a trial together with a promotion on an online shopping service using other payment method, such as e-banking, cash, micropayment, or convenience store service. The protected segment group was relatively young and inexperienced in online shopping service. The social participation segment group preferred to use the internet for social participation and cared about public notices. If a service designer is trying to target the protected segment or the social participation segment, then it should enhance security and IPR issues. The occasional segment group was not as young and had a lower use rate of online services, whereas they also used online shopping. Web sites could offer these users a friendly security service to attract their purchases.

Urban and rural differences

In order to study the similarities and differences between the online behavior patterns of each region, this study applied multiple contingency table analysis. The findings on the effects of regional differences made up Table IV, showing the conditional probabilities of each of the 11 types of use behavior within each individual-regional group (S_iT_j). Each of the ten individual-regional segments ($5S \times 2T = 10ST$) showed its own unique profile or combination of 11 online behaviors. Table IV showed that online shopping using a credit card or e-banking had obvious differences between urban and rural areas per individual segment. Other behaviors also had differences between urban and rural areas per individual segment, such as using the internet for work, sending/receiving mail, online shopping using cash, or other payment methods (i.e. micropayment and convenience store payment), online security sense, and online security ability. On the other hand, some behaviors showed less difference between urban and rural areas per individual segment, such as browsing news, searching for public notices, and IPR sense. Urban residents were familiar with using the internet and online shopping using a credit card. People in urban areas (T2) used online services more often than those in rural areas (T1). However, rural region residents used other payment methods (except credit cards) more often than urban region residents. This might be attributed to the fact that the infrastructures of urban areas are

Table IV.
Conditional probabilities showing regional differences of online behavior patterns

	Individual segment per regional segment										Pearson χ^2-test			
	S1T1	S1T2	S2T1	S2T2	S3T1	S3T2	S4T1	S4T2	S5T1	S5T2	S_iT1	S_iT2		
											χ^2	p-value	χ^2	p-value
Online behaviors					*Behaviors probabilities*									
I1	***72.97***	***69.38***	0.85	0.39	*0.00*	*0.70*	51.61	50.58	8.29	8.33	2,887.05	0.00	2,091.26	0.00
I2	99.89	99.68	99.61	99.09	100.00	100.00	100.00	100.00	5.16	6.20	5,454.19	0.00	4,542.82	0.00
I3	93.04	94.29	84.07	85.49	*63.95*	*68.03*	81.17	78.89	53.05	57.69	660.58	0.00	549.76	0.00
I4	*95.95*	*97.74*	79.12	78.76	65.70	69.31	96.01	96.40	*74.96*	*80.13*	644.12	0.00	628.04	0.00
I5	*50.66*	*57.41*	5.18	5.05	0.00	0.00	*2.55*	*4.50*	3.60	3.85	1,988.82	0.00	1,871.61	0.00
I6	52.14	52.62	***53.67***	***46.11***	0.75	0.70	1.77	2.70	4.38	3.84	1,837.99	0.00	1,387.50	0.00
I7	***35.14***	***28.04***	35.65	36.79	0.83	1.40	***1.66***	***0.51***	8.45	5.77	973.34	0.00	684.09	0.00
I8	27.36	27.64	44.70	44.43	0.25	0.35	1.88	0.90	4.85	4.06	1,156.18	0.00	847.28	0.00
I9	80.70	82.97	*77.73*	*81.37*	82.71	81.56	***84.16***	***79.95***	0.00	0.00	1,875.26	0.00	1,496.34	0.00
I10	*86.68*	*89.13*	79.12	80.31	66.78	68.49	67.96	67.44	19.87	15.81	1,079.37	0.00	1,132.89	0.00
I11	48.85	46.96	50.81	51.81	59.30	58.81	53.60	51.87	47.97	45.94	38.80	0.00	39.53	0.00

Pearson χ^2 test

	$S1T_j$		$S2T_j$		$S3T_j$		$S4T_j$		$S5T_j$	
	χ^2	p-value	χ^2	p-value	χ^2	p-value	χ^2	p-value	χ^2	p-value
I1	***6.20***	***0.01***	1.53	0.22	8.45	0.00	0.18	0.67	0.00	0.98
I2	1.99	0.16	2.26	0.13					0.54	0.46
I3	2.63	0.10	0.75	0.39	*3.69*	*0.05*	1.36	0.24	2.35	0.13
I4	*10.76*	*0.00*	0.04	0.85	2.97	0.09	0.17	0.68	*4.09*	*0.04*
I5	*18.23*	*0.00*	0.02	0.90			*4.80*	*0.03*	0.05	0.83
I6	0.09	0.76	***11.05***	***0.00***	0.02	0.90	1.67	0.20	0.20	0.66
I7	***23.27***	***0.00***	0.27	0.60	1.53	0.22	***4.91***	***0.03***	2.86	0.09
I8	0.04	0.84	0.01	0.90	0.17	0.68	2.86	0.09	0.39	0.53
I9	3.43	0.06	*3.89*	*0.05*	0.45	0.50	***5.08***	***0.02***		
I10	*5.67*	*0.02*	0.42	0.52	0.67	0.41	0.05	0.82	3.00	0.08
I11	1.42	0.23	0.19	0.66	0.05	0.82	0.50	0.48	0.45	0.50

Notes: I1, work need to use internet; I2, sending/receiving mail; I3:browsing news; I4, searching for public notices; I5, payment (credit card); I6, payment (online banking); I7, payment (cash); I8, payment (other); I9, security sense (refused open unknown email); I10, security capability (change password); I11, IPR sense; T1, rural region; T2, urban refion; S1, knowledge segment; S2, online shopping segment; S3, protected segment; S4, social participation segment; S5, ossasional segment. Bold and italics text presents the T1 use probabilities more than T2 (significant difference); underlined text presents the T2 use probabilities more than T1 (significant difference) more established. Users residing in rural areas have fewer options. Therefore, they are more used to traditional payment method. The user online behavior (11 online applications) were separated into various individual-regional groups (S_iT_j) and showed a significant difference (all p-values < 0.001). These results showed that regional differences certainly existed within the online behavior patterns.

Urban region residents were ability to use internet applications and online shopping using a credit card, but they hardly use other payment methods. For rural region residents, they usually preferred e-banking or cash, than credit card for online shopping. People in urban areas (T2) used online services more often than those in rural areas (T1). However, members of S4T1 and S5T1 (elder people residing in rural areas) had online security cognition and used online shopping services more often than those of S4T2 and S5T2 (elder people residing in urban areas). This might be attributed to the fact that rural areas had less established public facilities or infrastructure than urban areas had.

Conclusions

This study applied the MLCA model to investigate internet usage patterns from 11 online behaviors among 10,909 Taiwan residents as valid samples. This research took the regional effects and their personal characteristic variations into account for analysis, discussing the potential influence behind users' online behaviors, with the goal of aiding service providers in understanding and mastering their target users. The results categorized the online behavior patterns into five user segments: knowledge, online shopping, protected, social participation, and occasional. These five user segments showed distinct online behavior patterns. At level 2, the results categorized the population into two regional segments: urban and rural. These two regional segments of the composition were different. This paper found that both user segments and regional segments were highly interpretable, showing that online activities and e-payment behavior do exhibit certain identifiable patterns and regional differences. So the research propositions are proposed:

P1. For e-payment behavior patterns, urban and rural have significant differences.

The regional segments influenced the individual segments of different use patterns. For instance, the urban area comprised a higher proportion of members who were familiar with internet applications and online shopping using a credit card. On the other hand, people in rural area seldom used online services. Moreover, rural region residents used other payment methods (except using credit cards) more often than urban region residents. For both urban and rural regions, online users had more e-payment application experience and were equally concerned about the security ability. Interestingly, those who used many types of online applications paid less respect to IPR than those who used only a few types of applications:

P2. Personal characteristics influence online activities and e-payment behavior.

On the other hand, the user segments are dictated by users' activities and e-payment behaviors and personal characteristics. The result of the analysis indicated that factors such as age, income, gender, and online shopping expenses influenced online behaviors. For instance, younger people were familiar with various online services, and they had more online security capability than others. People with higher level of income spent relatively more for online shopping and often used various internet applications more than others. Female had relatively higher frequency for searching public notices. These results showed that online behavior patterns did exhibit regional differences, affected by personal characteristics:

P3. For online shopping and e-payment behavior, knowledgeable users were the majority of these activities.

Among individual segment members using the internet for work, online shopping using a credit card and e-banking, security sense, and online security ability had the most obvious differences between urban and rural areas. Knowledgeable users were the major users of online shopping applications, and web sites could offer these users discounts of customization to attract their purchases. Public service information can be promoted by cooperating with women topics online or online shops to increase the visibility of these messages.

Partnerships between users' personal characteristics and regional should prove valuable for urban and rural population segments by enabling various online functions. Urban and rural difference exists in the user behavior in e-payment services, with the main distribution of the knowledge segment in the urban segment. The online users of the urban segment are important clients in which online service providers should put more emphasis in the credit card e-payment method preferred by this segment.

Academic implications

In the social sciences, many studies investigate the construct relationship when both categorical outcomes and predictor variables are latent. Categorical data analysis is very useful in the analysis of sociological data. Hence, for a classification survey, scholars are more concerned about that the potential groups of samples and the latent class model with a better means to categorize data. Indeed, it is more appropriate to use latent class analysis in attitude or classification survey. Our study applied MLCA to attain regional segmentation and cross-region user segmentation. MLCA is a powerful model-based tool for both regular user segmentation and regional segmentation. This study took the methodology from previous scholars and applied MLCA to investigate user behavior patterns based on multilevel data structures. Our step-by-step analytical processes and outcomes can provide for academic reference in the future. These academic implications can be a useful guideline for future researches.

Managerial implications

To increase the number of users, service providers can offer an appropriate collocation of online shopping and additional payment methods, such as e-banking or cash, to attract purchases from rural region residents. The research results shows the more experienced users are with e-payment, the higher level of security sense, and online security ability these users have (the results are consistent between urban and rural areas). Another suggestion for the planning of e-payment services in the future is for the financial industry and online stores to offer different levels of data protection to choose from. By enforcing the e-payment safety and offering customization options, both potential customers and heavy users can be benefited. With these findings a service provider might identify its potential users in order to design the proper marketing strategies. Service providers can refer to the pattern of online behavior for their own development, which might be helpful to increase fitness and service satisfaction between products and users' needs.

This paper suggests that internet product or service providers could find more appropriate user clusters based on the characteristics of products. For instance, if a service designer is trying to target younger users, then it could use pre-introduction or a trial together with a promotion on an online shopping service using other payment method, such as e-banking, cash, micropayment, or convenience store service. Most users that are above 40 years old have security sense while engaging in online activities and e-payment behavior. However, these users seem to lack security capability. A suggestion is that programmers and web designers should design a user-friendly interface that takes into consideration this consumer segment and can gain their trust.

Future directions and research limitations

The methodology of MLCA on online behavior patterns requires a large cross-regional database which is why data collection can be difficult for researchers. Yet if future studies can extend this scope of study by carrying out longitudinal studies that observe the evolution of change in customer behavior it will greatly contribute to the understanding of how these behaviors change over time and help the service providers meet the users' needs. As this study has observed, adolescents are an important segment for online shopping. An interesting finding from our collected data shows that adolescent users are not as financially stable. Thus, it is difficult to identify a specific spending pattern among them. For future research, we suggest that to gain a deeper understanding on adolescent's purchase behavior, information on household income can also be analyzed. Finally, we suggest enlarging the variables and apply this study to different countries or region.

This study has some limitations. For instance, MLCA needs large amount of data to analyze. Hence, for a general study to implement its investigation, this may cause the big problem for research. Second, this study applied dichotomical questions (yes/no questions) in the main investigation. In questionnaire design, this is quite different with Likert 5 or 7 points scale. So the generalization of this study must be more conservative to apply to other fields or countries.

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Appendix

Regional segment	City/county	Individual segment S1	S2	S3	S4	S5	Subtotal
T1	Keelung City	68	46	29	30	16	189
	Yilan County	63	55	41	25	14	198
	Hsinchu County	84	43	42	41	23	233
	Miaoli County	88	55	48	44	20	255
	Taichung County	224	166	171	83	81	725
	Changhua County	182	116	120	97	64	579
	Nantou County	64	57	44	36	19	220
	Yunlin County	67	63	59	49	26	264
	Chiayi County	47	52	51	33	28	211
	Chiayi City	42	26	25	23	15	131
	Tainan County	140	114	85	89	70	498
	Tainan City	110	68	81	61	33	353
	Kaohsiung City	254	153	144	127	82	760
	Kaohsiung County	156	116	115	82	62	531
	Pingtung County	98	78	94	44	50	364
	Penghu County	12	8	7	6	3	36
	Hualien County	63	36	27	15	18	159
	Taitung County	40	29	14	10	12	105
	Kinmen County	15	9	7	7	3	41
	Leinchiang County	5	2	1	2	1	11
T2	Taipei City	674	174	188	208	111	1,355
	Taipei County	787	312	365	278	201	1,943
	Taoyuan County	393	161	169	146	97	966
	Hsinchu City	90	32	35	35	16	208
	Taichung City	228	92	100	110	44	574
Total		3,994	2,063	2,062	1,681	1,109	10,909

Table AI. The administrative region (of Taiwan) composition of the regional segments

CAIC 3 Number of individual segments	Number of regional segments 1	2	3
1[a]	127,658.29	127,668.59	127,678.88
2	120,995.41	120,966.18	120,975.28
3	118,367.23	118,313.79	118,313.86
4	117,894.19	117,839.57	117,844.56
5	***117,686.17***	***<u>117,610.15</u>***	***117,622.98***
6	117,721.46	117,644.52	117,677.03
7	117,727.35	117,706.83	117,712.06

Notes: The lowest BIC within each row is in italic and within each column is in boldface. The lowest BIC overall is underlined. [a]If $S = 1$, then the number of regional segments (T) is also restricted to 1 by definition

Table AII. Model fit (CAIC) for alternative numbers of regions and user segments

Table AIII.
Model fit (L2, *p*-value, Class.Err, LL, BIC(LL) and Npar) for alternative numbers of regions and user segments

Number of individual segments	L2	Model fit *p*-value	Class.Err	Number of regional segments								
				LL			BIC(LL)			Npar		
				1	2	3	1	2	3	1	2	3
1	12,422.838	3.1e−1,459	0.000	−63,772.51	−63,772.51	−63,772.51	127,647.29	127,656.59	127,665.88	11	12	13
2	5,636.390	3.6e−337	0.085	−60,379.29	−60,354.37	−60,348.63	120,972.41	120,941.18	120,948.28	23	25	27
3	2,884.640	0.000	0.146	−59,003.41	−58,961.25	−58,945.83	118,332.23	118,275.79	118,272.86	35	38	41
4	2,288.035	0.000	0.167	−58,705.11	−58,657.20	−58,639.10	117,847.19	117,788.57	117,789.56	47	51	55
5	1,956.446	0.690	0.230	−58,539.31	−58,475.56	−58,456.23	117,627.17	117,546.15	117,553.98	59	64	69
6	1,868.165	0.960	0.252	−58,486.90	−58,425.81	−58,411.18	117,633.91	117,567.52	117,594.03	71	77	83
7	1,750.487	1.000	0.274	−58,449.03	−58,390.03	−58,356.61	117,669.75	117,616.83	117,615.06	83	90	97

Cluster size	Wald	Models for Indicators p-value	R^2
Online behaviors			
Using the internet for work	1,068.93	0.00	0.44
Sending/receiving mail	445.51	0.00	0.89
Browsing news	874.59	0.00	0.11
Searching for public notices	513.48	0.00	0.10
Online shopping using a credit card	944.58	0.00	0.32
Online shopping using e-banking	760.06	0.00	0.29
Online shopping using cash	543.03	0.00	0.15
Online shopping using other payment methods	588.48	0.00	0.18
Online security sense	24.19	0.00	0.32
Online security ability	1,396.67	0.00	0.20
IPR sense	71.64	0.00	0.01
Regional segments			
T1 (72.65%)	26.38	0.00	
T2 (27.35%)	24.33	0.00	
Personal characteristic variables			
Age	589.69	0.00	
14 and younger			
15-20			
21-30			
31-40			
41-50			
51 and older			
Income (household income per month)	299.52	0.00	
Low (<US$1,714)			
Middle (US$1,714-2,742)			
High (> US$2,742)			
Uncertain (or refused to answer)			
Gender	20.54	0.00	
Female			
Male			
Online shopping expenses per year	1,026.52	0.00	
<US$171			
US$171-1,714			
More than US$1,714			
Uncertain			

Table AIV.
Models for indicators

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