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Regional differences of online learning behavior patterns

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Abstract

Purpose – The aim of this paper is to show that online learning behaviors are dictated by both personal characteristics and regional differences.

Design/methodology/approach – Data were collected from 16,133 users in 25 regions of Taiwan. The paper examined usage behaviors by looking at 11 items of categorical variables about online learning. This study implemented a multi-level latent class model to investigate online learning behavior patterns that exhibit regional differences.

Findings – The results showed that online learning patterns do exhibit regional differences, as the regional segments are dictated by the individual segments of different use patterns. For instance, the urban area segment comprised a higher proportion of members who are good at using the internet. The rural area segment made up a higher proportion of members who occasionally use the internet. Interestingly, rural users went online more often than urban users when in search of e-learning or entertainment. On the other hand, the individual segments are dictated by users' personal characteristics. For instance, younger people are good at employing online learning and entertainment services. Moreover, those who use many types of online applications pay less respect to intellectual property rights than those who only use a few types of applications.

Originality/value – By using a massive amount of survey data to show regional differences in online learning behavior patterns, the findings herein will help internet service providers form an applicable guideline for developing service strategies of higher service satisfaction between products and users' needs.

Keywords Regional difference, Online learning pattern, Learning, Taiwan, User studies, Individual behaviour

Paper type Research paper

1. Introduction

With the popularity of the digital environment, the internet is influencing people's daily lives more so than it did in the past. There are now plentiful, multi-dimensional, and convenient services that stimulate people to make changes in their lifestyle, and even their daily activities are gradually shifting from concrete circumstances into virtual ones. For example, bulletin boards have evolved into websites and personal diaries have transformed into blogs or micro-blogs, as the learning environment has migrated online from actual classrooms. People appear to be not doing anything particularly new – just doing old things in new ways and finding that some of those new ways suit their lifestyle better (Anderson and Tracey, 2001). The internet allows people who are already engaged in these activities to conduct them in different and sometimes more efficient ways (Selwyn *et al.*, 2005). The internet also more and more affects other aspects of life, such as family, learning, and work, and it has an ever-increasing influence among younger cohorts (Shah *et al.*, 2001).

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More people are now contributing to the generation of online applications, like movies, games, e-news, blogs, mobile phones, and e-learning (Shah *et al.*, 2001). Academic staff frequently use the internet to receive general teaching materials, as a referral to additional lecture materials, and to improve their access to scholarly resources (Nwezeh, 2009). Teachers are more eager to perform web-reinforced teaching and are expected to use blogs and social network sites in their own class instruction (Kiyici, 2010). Such changes induce internet service providers to value users' needs and their internet usage behaviors more so than before. Businesses must understand the user characteristics that influence user adoption of this medium for shopping (Citrin *et al.*, 2000). Data about users' online behavior are needed to help service providers define their online service strategies for website design, online advertising, market segmentation, product variety, inventory holding, and distribution (Lohse *et al.*, 2000).

If an internet marketer 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). For service providers, understanding and mastering user needs through user behaviors on 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 (Lohse *et al.*, 2000).

The internet is context-dependent with and highly variable between households and patterns of participation in the information society (Selwyn *et al.*, 2005; Anderson and Tracey, 2001). Users' behaviors are not independent when citizens reside in the same city or country, and environment and personal characteristics influence users' behaviors on the internet (Livingstone and Helsper, 2007; Mills and Whitacre, 2003). This study examined the extent to which there are cross-regional versus regional-specific user segments defined by behavioral patterns and whether groups of regions exist that are homogenous in their user segment structure. In particular, region segmentation is determined based on the relative sizes of cross-regional user segments. The simultaneous approach ensures that both regional-specific and cross-regional user segments can be accommodated. This paper investigated the usage behaviors by examining 11 items of categorical variables about online learning. Data were collected from 16,133 users in 25 regions of Taiwan. This study implemented a multi-level latent class model to investigate online learning behavior patterns that exhibit regional differences, with the goal of providing service providers an understanding and mastery of their target users.

2. Literature review

This section offers a review of typical online learning activities and the effecting variables so as to depict the background and motivation of this study.

2.1 Typical online learning activities

Internet applications and services enrich people's lives (Anderson and Tracey, 2001). The internet represents an extension of broader social roles and interests in the "offline" world (Colley and Maltby, 2008). While internet use is widely diffused in the global society, some people do not use the internet, some people cannot afford it, and some people do not use it well. However, for a rapidly growing number of people the internet is a valuable communication and information-gathering tool, and for others it is a vital part of their lives. What are typical online learning activities? The research results of Weiser (2001) showed that internet usage is principally motivated by the acquisition of goods and information.

According to research on internet usage patterns in the USA from some scholars like Howard, the chief purpose can be sorted into communication, fun, information utility, major life activities, and transactions (Howard *et al.*, 2001). Colley and Maltby (2008) revealed that the most common internet applications are communicating with friends, browsing news, acquiring general information, support for those with access/mobility problems, entertainment, product search information, online education, and job-search information. Some studies also showed that activities conducted through the internet comprise online communication, research, browsing news, downloading software, playing games, researching products and service information, entertaining, and educating (Sam *et al.*, 2005). Nwezeh (2009) stated that frequent usages of the internet include web browsing, discussion groups, news, and file transfers. Gross and Leslie (2009) stated that the new approach applications are blogs, RSS, image hosting, podcasting, social networking, and Wikipedia.

With copyright and government service challenges as new issues in the internet world, this paper also examined intellectual property rights and the provision of public services. This study categorized some online learning behaviors that occur frequently and chose 11 of them to analyze, encompassing browsing news, acquiring general information, browsing blogs, searching for product information, using the internet for entertainment purposes, searching for job information, e-learning, searching for public notices, internet connection through a public device, IPR (intellectual property rights), and internet connection through a mobile phone.

2.2 Online learning variables of location and personal characteristics

Opportunities, needs, motivations, material circumstances, and life experiences vary among people and therefore affect their extent or degree of participation or engagement in using the Internet (Selwyn *et al.*, 2005). Users who have more connection points through which to access the internet are more likely to use it for beneficial purposes, including seeking general information, researching products, and purchasing products (Hassani, 2006). The diffusion of the internet has occurred at the intersection of both international and within-country differences in socioeconomics (Chen and Wellman, 2004). The digital divide between rural and urban still influences how telecommunications and other advanced technologies are employed (Donnermeyer and Hollifield, 2003).

Socio-economic factors, such as higher average income and education level, affect the favorite usage of information and communications technology by urban communities, whereas rural communities are impacted by an inadequate telecommunications infrastructure that put them at a greater disadvantage (Cullen, 2003). Divergent regions have different infrastructures, economies, and populations, leading to environmental diversifications of location (Mills and Whitacre, 2003). Hence, this also affects the divergence in citizens' internet usage patterns (Wilson *et al.*, 2003). Users in the same region have the same background environment, and therefore when discussing online learning behaviors across different areas, like rural versus urban, researchers should take account of the environment, so that they can accurately compare the online behaviors of users from different regions. The findings from the scholars mentioned above and regional differences are herein referenced and analyzed.

In addition to location, other factors that influence online behaviors, such as users' social status, age, and gender, are also noted as major concerns in several research studies (Teo, 2001). For example, Livingstone and Helsper (2007) showed that 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 and age have significant influences (Wasserman and Richmond-Abbott, 2005). 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). Hargittai and Hinnant (2008) suggested that user attributes reveal that online skill is an important mediating factor in the types of people's online activities. Teo and Lim (2000) proved that different genders and age levels had a significant impact on online use patterns, such as time spent over one day browsing or downloading.

Personal characteristics affect internet use, such as duration of internet usage access time, motivation for using the internet, internet skill acquisition, frequency of internet use, and evaluation of internet information content (Akporido, 2005). Korupp and Szydlik (2005) discovered that social capital issues such as age, gender, and residence are more important than economic capital in explaining private internet use. Hargittai and Hinnant (2008) stated that online use pattern differences are large among the population of young adult internet users. The current study referenced the findings from the scholars mentioned above and took some personal characteristic variables such as age, access time, and gender into the research model to analyze how these personal characteristic variables influence the pattern of online learning.

2.3 Multi-level latent class analysis (MLCA)

In the social sciences, many research topics have investigated the relationship when both categorical outcomes and predictor variables are latent. Categorical data analysis has indeed been very useful in the analysis of sociological data (Goodman, 2007). For an attitude or classification survey, researchers are generally more concerned about the potential group of samples, and the latent class model 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; Horn *et al.*, 2008). A latent class model assumes that the population of subjects is divided into a few exclusive latent classes. Latent class analysis (LCA) is a statistical method used to identify the subtypes of related cases by using a set of categorical and/or continuously observed variables. These subtypes are referred to as latent classes. The classes are inferred from multiple observed indicators and are not directly observed (Bijmolt *et al.*, 2004; Henry and Muthén, 2010).

Traditional LCA assumes that observations are independent of one another, but multilevel data structures are common and needed in social and behavioral research. For example, observations are not independent when the data structure includes citizens nested in a city, employees nested in companies, or students nested in schools. The consideration and assessment of contextual level predictors in a LCA framework have implications for many salient research questions in the social and behavioral sciences. These nested data structures require multilevel techniques. In response to these needs, scholars have presented a framework for assessing latent class models with nested data (Bijmolt *et al.*, 2004; Henry and Muthén, 2010; Vermunt, 2003). Multi-latent class analysis (MLCA) has been suggested as a model-based tool for both regular user segmentation (individual level; level 1) and regional segmentation (contextual level; level 2) (Bijmolt *et al.*, 2004; Henry and Muthén, 2010; Horn *et al.*, 2008; Vermunt, 2003). The parameters of the MLCA model can be estimated by maximum likelihood, in which the maximization of the likelihood function is achieved by an adapted version of the expectation-maximization (EM) algorithm (Bijmolt *et al.*, 2004; Vermunt, 2003). Estimations are obtained for fixed numbers of regional segments (T) and user segments (S). Appropriate values for these numbers are then determined by estimating the MLCA for different values of T and S, and by examining the relative fit of alternative model specifications, for example by using the minimum BIC rule (Henry and Muthén, 2010; Horn *et al.*, 2008; Vermunt, 2003). This study applies MLCA to attain the segmentation of multi-level data structures.

2.4 Investigating user behavior patterns

Some scholars have indicated that understanding user behaviors on the internet is helpful for product research and development, together with sales (Lohse *et al.*, 2000). Changchien *et al.* (2004) stated that due to the diversity in individual usage behaviors, cognitive needs and personality, further research into methods of clustering users may be quite interesting and helpful. Some studies suggested sorting online use patterns by users' age (Shah *et al.*, 2001), while others explored the length of experience, access time, and frequency of online use patterns (Akporido, 2005; Donnermeyer and Hollifield, 2003; Nwezeh, 2009). Other than taking up the descriptive statistics, researchers also surveyed using user behavior factor analysis to investigate usage patterns among various users (Teo, 2001; Torkzadeh and Dhillon, 2002).

Another way to examine which people conduct what type of online activities is to explore user typologies. Scholars have discovered differences among time, frequency, and range of internet usage (Katz *et al.*, 2001; Selwyn *et al.*, 2005). Although the length of experience and frequency of online use are useful predictors of which activities people do online (Howard *et al.*, 2001), the patterns of online learning also prove to be a significant predictor. This study aims to test such a particular relationship of types of online usages. This study took its methodology from previous works and applied multi-level latent class analysis to investigate user behavior patterns based on multi-level data structures (Bijmolt *et al.*, 2004; Henry and Muthén, 2010; Horn *et al.*, 2008).

3. Objective and methodology

This study simultaneously applied multi-level latent class analysis to attain regional segmentation (T; level 2) and cross-region user segmentation (S; level 1). The multi-level latent class methodology is available in the computer program LatentGOLD v4.0 (Vermunt and Magidson, 2005). This study implements SPSS v12.0 to collate data descriptive statistics and the contingent table.

3.1 Objectives of this study

The study had as its goal to attempt to answer the following questions:

- Do online learning behaviors exhibit city or county differences?
- Do online learning behaviors exhibit certain identifiable patterns?
- Can cities or counties be clustered into a more abstract typology (based on multi-level data structures)?
- How do personal characteristic variables affect online learning behavior patterns?
- Do online learning patterns exhibit regional differences?
- What kind of special or interesting online learning differences exist in urban/rural regions?

3.2 Sample

Taiwan's internet prevalence is rather high. In 2009 the average percentage of household internet access was 78.1 percent, with average daily time spent on the internet of 2.95 hours (Research, Development and Evaluation Commission, 2009). Such data are equal to 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), South Korea (81.1 percent), and Singapore (77.8 percent) (Miniwatts Marketing Group, 2010). Therefore, the surveyed data of online learning that Taiwanese residents possess could be a reference to some extent and could also 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. This annual survey includes three parts:

(1) information and communications technology environment;

(2) skills to use the internet; and

(3) internet usage behaviors.

The survey was conducted by computer and telephone interviews from July to August 2009. Random sampling interviews were used on a segmented population of interviewees from age 12 and above in 25 counties and cities. The survey collected 16,133 valid random samples with a response rate of 66.4 percent, and the sampling errors never exceeded ± 4 percent. This study used 11 items of categorical variables about online learning behavior as a research dataset. The data are used in exclusion of missing values for the 10,909 valid samples.

Social science research using user-level data is typically based on regional samples that are not proportional to actual population sizes. If one requires conclusions out of the entire cross-region population, then re-weighting would be necessary to ensure that the pooled sample accurately represents the population (Vermunt, 2003; Bijmolt *et al.*, 2004). To achieve valid inferences in the multi-level latent class analysis, this study weights each observation by sample size according to the population by gender, age, and each region.

3.3 Indicators of this study

Eleven categorical indicators are used to inform latent class membership (1 = yes, 0 = no):

(1) browsing news;
(2) acquiring general information;
(3) browsing blogs;
(4) searching for product information;
(5) using for entertainment purposes;
(6) searching for job information;
(7) e-learning;
(8) searching for public notices;
(9) internet connection through a public device;
(10) IPR sense (when one gets data from the internet for personal use that still needs to consider copyright issues); and
(11) internet connection through a mobile phone.

This paper considered latent classes of online learning among 10,909 Taiwan residents who live in one of 25 different regions. This data structure represents a nested or multi-level design in which individuals show a level 1 in the hierarchy and regions represent level 2. This study took both individual- and contextual-level predictors of online learning behaviors' typologies. Tables I and II show descriptive statistics for the internet use sample.

3.4 Assessing the city/county effects

Do online learning behaviors exhibit city or county differences? To assess the significance of the city/county effects, we employ the likelihood ratio χ^2 test for online learning behaviors. The city or county variables significantly affect some (seven out of 11) of the online learning behaviors: browsing news, acquiring general information, searching for product information, e-learning, searching for public notices, internet connection through a public device, and internet connection through a mobile phone. Table III reports city/county effects for each online learning behavior, showing that online learning behaviors probably exhibit some differences among cities and counties. This study took this result and used MLCA to investigate further whether regional differences exist within the online learning behavior patterns.

3.5 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 above. This paper incorporated the effects from three personal characteristic variables (i.e. age, access time, and gender) by means of concomitant variables. Model estimates are obtained for alternative numbers of user segments ($S = 1, \ldots, 4$) and regional segments ($T = 1, 2$). Table IV reports model fit (in particular, the BIC value) for each combination of S and T. The optimal number of user segments

Table I.
Descriptive statistics for the online behavior sample

Region	Sample size	Average weight	Online behavior (sample proportion)										
			Browsing news	Acquiring general information	Browsing blogs	Searching for product information	Using for entertainment purposes	Searching for job information	E-learning	Searching for public notices	Internet connection through a public device	IPR sense	Internet connection through a mobile phone
Taipei City	813	2.28	86.7	91.2	78.7	75.1	73.3	80.7	30.6	90.3	67.3	51.5	24.6
Taipei County	818	3.32	81.5	90.5	77.1	70.4	74.1	76.9	28.6	87.3	64.5	48.7	20.2
Keelung City	601	0.46	80.4	88.9	79.4	74.6	76.2	79.4	32.1	85.2	61.4	54.2	19.0
Yilan County	603	0.53	80.2	90.4	78.2	71.6	78.3	78.8	35.4	81.3	63.5	52.3	19.2
Taoyuan County	812	1.65	81.0	88.5	74.6	72.2	77.6	78.1	30.6	86.2	60.0	50.8	24.6
Hsinchu County	608	0.56	81.1	84.1	79.0	70.5	75.1	79.9	32.6	83.3	61.4	49.8	19.2
Hsinchu City	607	0.45	82.2	89.4	78.4	72.1	74.5	80.3	30.8	86.1	65.4	49.0	18.8
Miaoli County	603	0.64	83.2	87.9	71.9	63.3	75.8	80.9	34.4	82.4	59.8	53.1	20.3
Taichung County	602	1.80	77.5	86.9	74.3	65.5	78.2	80.2	27.7	82.6	61.3	49.0	21.6
Taichung City	800	0.93	80.5	88.7	79.6	72.9	72.3	80.3	28.3	90.1	65.3	53.1	19.5
Changhua County	600	1.53	76.6	87.9	80.3	62.7	74.1	77.6	28.3	84.5	60.8	48.9	20.2
Nantou County	605	0.61	77.7	89.1	79.5	66.4	75.5	79.1	34.1	82.3	61.4	51.4	20.0
Yunlin County	604	0.83	75.5	84.9	78.9	64.5	81.5	80.0	34.0	84.5	58.9	54.0	20.4
Chiayi County	602	0.64	74.9	87.7	73.0	65.4	73.9	74.9	30.8	82.5	60.7	53.6	19.4
Chiayi City	606	0.32	82.4	90.2	79.4	67.9	77.3	81.7	34.4	86.3	62.1	57.3	19.7
Tainan County	600	1.32	79.1	84.9	72.7	63.9	76.4	77.7	26.1	83.2	57.1	55.6	16.4
Tainan City	603	0.88	78.5	83.3	73.9	67.1	76.2	78.2	31.2	87.3	63.5	52.1	19.5
Kaohsiung City	800	1.35	81.4	84.7	75.3	63.8	72.8	78.3	33.6	83.8	58.6	50.2	19.0
Kaohsiung County	605	1.44	78.4	84.4	77.0	64.1	72.4	74.0	31.0	82.9	60.9	54.1	15.6
Pingtung County	601	1.04	75.8	81.9	73.6	58.5	78.6	75.3	26.6	83.0	53.6	54.1	13.2
Penghu County	608	0.11	82.9	91.4	77.8	66.7	80.0	80.0	40.0	83.3	63.9	51.4	22.2
Hualien County	606	0.40	80.4	90.6	75.9	70.3	76.6	80.4	41.1	84.8	63.9	53.8	19.6
Taitung County	605	0.27	79.8	89.4	78.8	67.3	74.0	73.1	33.7	88.5	57.7	51.9	19.2
Kinmen County	602	0.11	90.0	87.5	80.0	67.5	80.0	77.5	35.0	90.0	65.0	52.5	17.5
Leinchiang County	619	0.03	90.0	90.9	80.0	72.7	81.8	81.8	45.5	90.0	72.7	45.5	27.3
Total	16,133		80.6	88.0	76.7	68.5	75.1	78.3	30.4	85.8	62.2	51.3	20.3

Characteristic	Percentage of respondents
Age	
14 and younger	6.9
15-20	13.9
21-30	25.9
31-40	23.9
41-50	18.5
51 and older	10.9
Gender	
Female	48.3
Male	51.7
Access time (minutes per day)	
30 and less	8.5
31-60	15.9
61-120	20.2
121-180	14.5
181-300	15.5
301 and more	13.0
Contingent	12.5

Table II. Descriptive statistics for the online behavior sample: personal characteristics

Online behaviors	Likelihood ratio χ^2 test χ^2	*p*-value
Browsing news	70.09	0.00
Acquiring general information	73.57	0.00
Browsing blogs	33.19	0.10
searching for product information	101.61	0.00
Using for entertainment purposes	30.25	0.18
Searching for job information	24.43	0.44
E-learning	39.19	0.03
Searching for public notices	68.38	0.00
Internet connection through a public device	51.43	0.00
IPR sense	21.17	0.63
Internet connection through a mobile phone	54.00	0.00

Table III. City/county effects upon online learning behavior

applied the minimum BIC (Henry and Muthén, 2010; Horn *et al.*, 2008; Vermunt, 2003). The overall minimum BIC is attained at four user segments and two regional segments (BIC = 122106), which this study identified as the most appropriate solution. The study also checked the reports' model fit through the result of the Wald test (Buse, 1982; Wald, 1943). The Wald value of the model for regional clusters (25 cities/counties in level 2; T1 = 89.44, p-value <0.001; T2 = 136.47, p-value <0.001) means the contextual level is divided into two segments (T) with a significant difference (Agresti, 2007; Wald, 1943). In addition, the individual level (level 1 has 11 online learning applications among 10,909 users) is divided into four segments (S) and also shows a significant difference (all p-values <0.001). Three personal characteristic (covariate) variables significantly affect the individual level: age (Wald = 1136.78, $p < 0.001$), access time (Wald = 878.95,

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

Number of individual segments (S)	Number of regional segments (T) 1	2	3
1[a]	*130,821*	130,831	130,840
2	123,378	*123,359*	123,369
3	*122,768*	122,778	122,777
4	**122,149**	***122,106***	**122,134**
5	122,161	*122,112*	122,135
6	122,176	*122,127*	122,195
7	122,215	*122,201*	122,223

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

$p < 0.001$), and gender (Wald = 23.22, $p < 0.001$). Therefore, this study divided the user level (S) into four segments and the regional level (T) into two segments, which altogether induced the most appropriate solution.

4. Results

4.1 User and regional segmentation

Do online learning behaviors exhibit certain identifiable patterns? Tables V-VII present online learning behaviors within each user segment. The tables show that the study acquired conditional probability for this research target, which consists of 11 online user behaviors. At the individual level, this paper discovered that the learning behavior patterns of the internet consist of four segments (referred to as S1 to S4), which show distinctive usage patterns.

Can cities or counties be clustered into a more abstract typology? Table VII presents the model's results linking regional and user segments. Taiwan is divided into two regional segments (referred to as T1 and T2), where segment probabilities represent the relative sizes within a regional segment, and the population size of each group is 85.54 percent and 14.46 percent, respectively. In order to deduce interpretation, this paper offers 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 to S4) was 47.9 percent, 30.3 percent, 12.4 percent, and 9.4 percent (total = 100 percent), respectively. Based on the individual level (four segments) and the contextual level (two segments), this paper has summarized the multi-contingency by a table of regional segments, user segments, and administrative regions of Taiwan (see the Appendix). Regional Segment 1 (T1) includes relatively more rural areas, and most of the local governments therein focus on agricultural or tourist development. This class was categorized as the rural

Table V.
Model results: individual segments

	Segment S1	S2	S3	S4
Cluster size (percent)	40.58	30.47	17.23	11.72

Online learning behavior	Behavior probabilities			
Browsing news	0.97	0.83	0.62	0.43
Acquiring general information	0.99	0.94	0.77	0.50
Browsing blogs	0.98	0.63	0.87	0.22
Searching for product information	0.96	0.70	0.36	0.17
Using for entertainment purposes	0.95	0.51	0.95	0.41
Searching for job information	0.96	0.73	0.81	0.25
E-learning	0.47	0.18	0.30	0.04
Searching for public notices	0.93	0.96	0.58	0.74
Internet connection through a public device	0.78	0.64	0.44	0.30
IPR sense	0.46	0.54	0.61	0.50
Internet connection through a mobile phone	0.33	0.11	0.16	0.06

Table VI. Model results: behavior probabilities

	Relative sizes of individual segments				Likelihood ratio χ^2 test	
Regional segments	S1	S2	S3	S4	χ^2	*p*-value
T1 (85.54 percent)	0.393	0.305	0.305	0.121	92.09	0.00
T2 (14.46 percent)	0.479	0.303	0.124	0.094		

Table VII. Model results: regional segments

segment. Regional Segment 2 (T2) includes relatively higher concentrations and a more complete infrastructure. This class was categorized as the urban segment. The findings from the regional segments of the user segment ingredients are shown in Figure 1. This paper has referenced the practice of Henry and Muthén (2010). These two regional segments of the composition are different.

4.2 Effect of personal characteristic variables

Users' online behaviors and thereby membership of user segments are often related to personal characteristic variables such as age, access time, and gender. How do personal characteristic variables affect online learning behavior patterns? This paper assessed the effects of three personal characteristic variables:

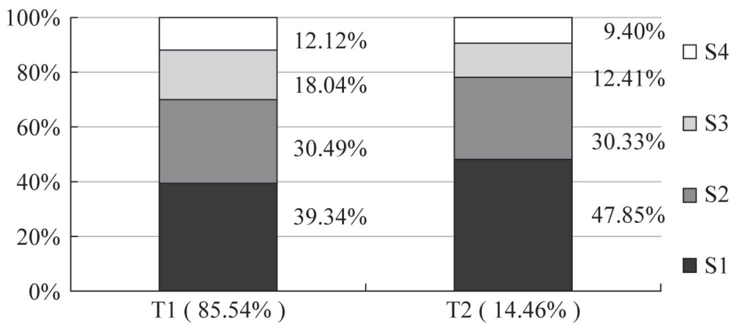

Figure 1. Multilevel latent class solution

(1) age;
(2) access time; and
(3) gender.

Ages included 14 and under, 15-20, 21-30, 31-40, 41-50, and above 51 for six species. The access time (minutes per day) included less than 30, 31-60, 61-120, 121-180, 181-300, and more than 301, and it was contingent for seven species. Table VIII presents the findings for the effects of personal characteristic variables. In order to deduce further interpretation, this paper has referred to the practice by Bijmolt *et al.* (2004). This paper does not present logic parameters, but instead segments membership probability per category of each personal characteristic variable, averaged across all categories of the other variables. For example, the rate of males in each user segment (S1 to S4) was 41 percent, 28 percent, 19 percent, and 12 percent (total = 100 percent), respectively.

4.3 Full model estimated

Do online learning patterns exhibit regional differences? The probability that a user belongs to a particular segment is modeled to depend upon his/her personal characteristics and on regional segmented membership. To assess the significance of the personal characteristic effects, we employed the likelihood ratio test for nested models. The right-hand side of Table VIII shows that all three personal characteristic variables significantly affected user segment membership: age ($\chi^2 = 8,141.13$; df = 15; p-value <0.001), access time ($\chi^2 = 3,184.19$; df = 18; p-value <0.001), and gender ($\chi^2 = 51.24$; df = 3; p-value <0.001). To further assess the significance of the

	Relative sizes of individual segments				Likelihood ratio χ^2 test	
Personal characteristic variables	S1	S2	S3	S4	χ^2	p-value
Age					8,141.13	0.00
14 and younger	0.10	0.00	0.80	0.10		
15-20	0.43	0.00	0.55	0.03		
21-30	0.66	0.13	0.13	0.07		
31-40	0.46	0.44	0.02	0.09		
41-50	0.25	0.56	0.01	0.18		
51 and older	0.10	0.58	0.00	0.32		
Access time (minutes per day)					3,184.19	0.00
30 and less	0.10	0.51	0.11	0.28		
31-60	0.24	0.48	0.15	0.12		
61-120	0.40	0.35	0.19	0.06		
121-180	0.56	0.18	0.21	0.05		
181-300	0.61	0.16	0.19	0.04		
301 and more	0.65	0.16	0.16	0.02		
Contingent	0.16	0.32	0.15	0.37		
Gender					51.24	0.00
Female	0.40	0.33	0.15	0.11		
Male	0.41	0.28	0.19	0.12		

Table VIII.
Model results: effects of personal characteristic variables

individual segment effects, Table VII shows that the regional segment variables significantly affect individual segment (user segment) membership ($\chi^2 = 92.09$; df $= 3$; p-value < 0.001). We concluded from these results that online learning patterns do exhibit regional differences and are affected by personal characteristics.

5. Discussion

This study took the contextual effect influenced by areas and their personal characteristic variations into account for analysis. Table VI shows the conditional probabilities of each of the 11 types of usage behavior within each individual segment (S1-S4, level 1). By considering some personal characteristic variables such as age, access time, and gender, this paper divided user segmentation at the individual level into four groups and regional segmentation at the contextual level into two clusters, gaining striking and significant results. In short, the clusters identified in this research (S1-S4 and T1-T2) effectively partition the online learning patterns among 10,909 users. It also took into account the potential classification of the usage model behind the personal characteristic variables.

5.1 Online user behavior pattern

User segmentation in each model of users' online behaviors is not the same. Through Figure 1 and Tables V-VIII this paper summarizes a more detailed classification of users' online behaviors. Considering the contextual level (regional) and personal characteristic variables, four patterns of users' online behaviors (user segments S1 to S4) are stated as follows.

- S1 – This segment consists of 41 percent of the total sample, chiefly composed of those aged 21-40. The majority of them spent three hours or more on the internet per day. This group was knowledgeable on various internet applications, such as browsing news (97 percent), researching general information (99 percent), browsing blogs (98 percent), searching for product information (96 percent), using for entertainment purposes (95 percent), searching for job information (96 percent), and searching for public notices (93 percent). Within this group, 78 percent have experienced internet connection through a public device, 47 percent of them have used e-learning, and their internet connection through a mobile phone is even up to 33 percent – these were the highest conditional probabilities of all segments. Interestingly, only 46 percent of them had any sense of intellectual property rights (IPR) – this was the lowest conditional probability of all segments. This group had more men than women. Their contextual level (regional segment) had a maximum number in the urban segment. This group was categorized as the knowledge segment.
- *S2* – This segment consists of 30 percent of the total sample, chiefly composed of those aged 31-50 and none under the age of 20. They had relatively low internet use, mostly under 60 minutes per day. They were good at using the internet for information research related to current events and social participation, such as acquiring general information (94 percent), browsing news (83 percent), and searching for product information (70 percent). They were also good at online searching for public notices (96 percent) – this was the highest conditional

probability of all segments. They relatively had more sense of IPR (54 percent) and more often had an internet connection through a public device (64 percent). They had relatively lower frequencies to use the internet for entertainment (51 percent), and less than 20 percent of them used e-learning and internet connection through a mobile phone. This segment had a higher proportion of women. Their contextual level resided evenly in each regional segment. This group was categorized as the social participation segment.

- *S3* – This segment consists of 17 percent of the total sample. The majority of them spent one to three hours on the internet per day. Most were young and skilled in using amusement services such as entertainment (95 percent) and browsing blogs (87 percent). More than 61 percent had a sense of IPR – this was the highest conditional probability of all segments. Their use of e-learning and searching for job information was relatively high (30 percent and 81 percent), whereas their internet connection through a mobile phone (16 percent) was also significantly prominent. They did not relatively care about public notices (58 percent) – this was the lowest conditional probability of all segments. Males had a high probability in this segment. Their contextual level (regional segment) had a maximum number in the rural segment. This group was categorized as the active segment.
- *S4* – This segment consists of 12 percent of the total sample. They were not young. They used internet applications relatively less, such as acquiring general information (50 percent), browsing news (43 percent), and searching for public notices (74 percent). They rarely had an internet connection through a public device (30 percent). Only 4 percent of them used e-learning, 6 percent had experienced internet connection through a mobile phone, and less 25 percent of them were browsing blogs, searching for product information, and searching for job information. This segment had a higher proportion of men. Their contextual level (regional segment) had a maximum number in the rural segment. This group was categorized as the occasional segment.

These four user segments showed distinctive online learning behavior patterns. The knowledge segment's members were knowledgeable on various internet applications, but were also more ignorant of intellectual property rights than others. The social participation segment's members preferred to use the internet for social participation and most cared about public notices and relatively less about entertainment. The active segment's members were relatively young and skilled in using entertainment services and had a greater sense of intellectual property rights than others. The occasional segment's members were not young and had a lower usage rate of online applications.

The individual segments are dictated by users' personal characteristics. Age and access time had a large influence on the user segment probabilities. For instance, younger people were good at employing e-learning and entertainment services. Older people were less attentive to trendy online applications, such as browsing blogs and internet connection through a mobile phone. Most of the knowledgeable users spent relatively more time accessing the internet than others. Most of the occasional users had uncertain online access times and were rather unfamiliar with internet applications. Of the demographics included here, gender had the smallest impact, as shown by the χ^2 test values and the differences between the segment membership probabilities. Generally speaking, males were relatively energetic users of entertainment applications, while females had a comparative concern for public service.

5.2 Regional differences

The regional segments are dictated by the individual segments of different use patterns. For instance, the urban area segment comprised a higher proportion of members who were good at using the internet. The rural area segment made up a higher proportion of members who occasionally used the internet. These two regional segments of the composition are different.

What kind of special or interesting online learning differences exist in urban/rural regions? In order to study the similarities and differences between the online learning behavior patterns of each region, this study applied multiple contingency table analysis. Table IX presents the findings on the effects of regional differences. This table shows the conditional probabilities of each of the 11 types of usage behavior within each individual-regional group (S_iT_j). Each of the eight individual-regional segments (4S*2T = 8ST) shows its own unique profile or combination of 11 online learning behaviors.

Table IX shows that various individual segments using the internet to search product information, browse blogs, and for entertainment purposes had the most obvious differences between urban and rural areas. Some behaviors also presented differences between urban and rural areas, such as browsing news, acquiring general information, searching for job information, e-learning, searching for public notices, and internet connection through a public device. Some behaviors had fewer differences between urban and rural areas, such as having a sense for IPR and an internet connection through a mobile phone. These results show that regional differences certainly existed within the online learning behavior patterns.

Urban region residents in general were good at using the internet for searching, but they used it relatively less often for online learning and entertainment. Perhaps due to insufficient infrastructure and traffic inconvenience, rural region residents used the internet more frequently for e-learning or entertaining. Generally speaking, people in urban areas (T2) used online services more often than those in rural areas (T1). However, members of S4T1 (occasional internet users residing in rural areas) generally used online services more than those of S4T2 (occasional internet users residing in urban areas). This might be attributed to the fact that the public facilities or infrastructure in rural areas are less established than those in urban areas. Those occasional users residing in urban areas who were familiar with Internet applications may have other choices, while rural region residents have fewer options.

6. Conclusions

This study has applied the MLCA model to investigate internet usage patterns from 11 online learning applications among 10,909 Taiwan residents who live in one of 25 different regions. This study 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

Table IX.
Conditional probabilities showing regional differences of online learning behavior patterns

Online behaviors	Behavior probabilities: individual segment per regional segment T								Likelihood ratio chi-square test			
									T1		T2	
	S1T1	S1T2	S2T1	S2T2	S3T1	S3T2	S4T1	S4T2	χ^2	*p*-value	χ^2	*p*-value
Browsing news	98.18	97.37	82.02	86.96	59.14	54.50	38.87	45.83	2331.81	0.00	403.92	0.00
Acquiring general information	99.13	99.13	94.05	93.80	75.66	78.00	45.72	44.64	2029.96	0.00	385.50	0.00
Browsing blogs	98.80	98.25	60.96	64.50	86.10	92.04	17.61	14.29	3553.58	0.00	732.77	0.00
Searching for product information	97.12	97.05	68.11	71.63	31.11	33.50	13.08	11.24	4256.99	0.00	806.06	0.00
Using for entertainment purposes	96.39	95.52	47.79	43.57	95.37	97.00	41.49	34.32	3162.79	0.00	763.04	0.00
Searching for job information	96.71	98.36	71.83	70.08	80.73	82.59	19.54	21.43	2669.41	0.00	599.53	0.00
E-learning	47.16	46.78	17.90	13.51	30.37	28.50	3.12	2.98	1167.87	0.00	293.72	0.00
Searching for public notices	93.07	94.86	96.09	95.97	56.08	60.00	70.90	79.17	1478.56	0.00	202.52	0.00
Internet connection through a public device	78.00	79.13	62.00	66.51	41.54	47.50	28.60	22.62	1161.90	0.00	237.11	0.00
IPR sense	45.15	49.07	55.04	50.54	60.41	69.50	47.73	52.38	130.03	0.00	29.02	0.00
Internet connection through a mobile phone	32.49	36.28	9.56	11.78	16.00	15.92	5.94	2.98	709.53	0.00	196.09	0.00

understanding and mastering their target users. This paper categorized the online learning patterns into four user segments:

(1) knowledge;
(2) social participation;
(3) active; and
(4) occasional.

These four user segments showed distinct online learning behavior patterns. At level 2, this paper categorized the population into two regional segments, i.e. urban and rural. These two regional segments of the composition were different. This paper found that results from both user segments and regional segments are highly interpretable, showing that online learning patterns do exhibit regional differences.

The user segments are dictated by users' online learning behaviors and personal characteristics. The results of the analysis indicate that age, access time, and gender influenced online learning behaviors. For instance, younger people were good at employing e-learning and entertainment services. Most knowledgeable users spent relatively more time accessing the internet than others. Males used the internet more often for online entertainment applications than females. Interestingly, those who used many types of online applications pay less respect to intellectual property rights than those who only used a few types of applications. On the other hand, the regional segments are dictated by the user segments of different use patterns. For instance, the urban area comprised a higher proportion of members who were good at using the internet. The rural area made up a higher proportion of members who occasionally used the internet. Moreover, rural region residents conducted online learning and entertaining more often than urban region residents.

This paper has suggested that internet products 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 implement a pre-introduction or a trial together with a promotion on a trendy online application, such as an entertainment, blog, or mobile phone service. People aged 21-40 were the major users of online applications, and websites could offer these users appropriate copyright rules and discounts of customization to attract their purchases. Partnerships between users' personal characteristics and regional and environmental characteristics should prove valuable for urban and rural population segments by enabling various online learning functions. Among individual segment members using the internet for browsing blogs, searching for product information and entertainment had the most obvious differences between urban and rural areas. Service providers can offer an appropriate collocation of local product information, customized interaction blogs, and a trial together with promotions on entertainment applications in order to attract purchases. If a publisher or service provider is trying to target urban residents, then it should enhance job-related information and interaction blogs and could use a pre-introduction or a trial together with a promotion on a mobile service. In a rural region, websites would benefit from offering more learning applications, entertainment services, and delivery services so that rural residents could conduct more purchases. 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 help to increase fitness and service satisfaction between products and users' needs.

References

Agresti, A. (2007), *An Introduction to Categorical Data Analysis*, Wiley, Hoboken, NJ.

Akporido, C.E. (2005), "Internet use in a Nigerian suburban setting", *The Electronic Library*, Vol. 23 No. 3, pp. 302-10.

Anderson, B. and Tracey, K. (2001), "Digital living: the impact (or otherwise) of the internet on everyday life", *The American Behavioral Scientist*, Vol. 45 No. 3, pp. 456-75.

Bijmolt, T.H.A., Paas, L.J. and Vermunt, J.K. (2004), "Country and consumer segmentation: multi-level latent class analysis of financial product ownership", *International Journal of Research in Marketing*, Vol. 21 No. 4, pp. 323-40.

Buse, A. (1982), "The likelihood ratio, Wald, and Lagrange multiplier tests: an expository note", *The American Statistician*, Vol. 36 No. 3, pp. 153-7.

Changchien, S.W., Lee, C.F. and Hsu, Y.J. (2004), "On-line personalized sales promotion in electronic commerce", *Expert Systems with Applications*, Vol. 27 No. 1, pp. 35-52.

Chen, W. and Wellman, B. (2004), "The global digital divide – within and between countries", *IT & Society*, Vol. 1 No. 7, pp. 39-45.

Citrin, A.V., Sprott, D.E., Silverman, S.N. and Stem, D.E. (2000), "Adoption of internet shopping: the role of consumer innovativeness", *Industrial Management & Data Systems*, Vol. 100 No. 7, pp. 294-300.

Colley, A. and Maltby, J. (2008), "Impact of the internet on our lives: male and female personal perspectives", *Computers in Human Behavior*, Vol. 24 No. 5, pp. 2005-13.

Cullen, R. (2003), "The digital divide: a global and national call to action", *The Electronic Library*, Vol. 21 No. 3, pp. 247-57.

Donnermeyer, J.F. and Hollifield, C.A. (2003), "Digital divide evidence in four rural towns", *IT & Society*, Vol. 1 No. 4, pp. 107-17.

Goodman, L.A. (2007), "Statistical magic and/or statistical serendipity: an age of progress in the analysis of categorical data", *Annual Review of Sociology*, Vol. 33, pp. 1-19.

Gross, J. and Leslie, L. (2009), "Learning 2.0: a catalyst for library organizational change", *The Electronic Library*, Vol. 28 No. 5, pp. 657-68.

Hargittai, E. and Hinnant, A. (2008), "Digital inequality differences in young adults' use of the internet", *Communication Research*, Vol. 35 No. 5, pp. 602-21.

Hassani, S.N. (2006), "Locating digital divides at home, work, and everywhere else", *Poetics*, Vol. 34 Nos 4/5, pp. 250-72.

Henry, K.L. and Muthén, B. (2010), "Multilevel latent class analysis: an application of adolescent smoking typologies with individual and contextual predicators", *Structural Equation Modeling: A Multidisciplinary Journal*, Vol. 17 No. 2, pp. 193-215.

Horn, M.L.V., Fagan, A.A. and Jaki, T. (2008), "Using multilevel mixtures to evaluate intervention effects in group randomized trials", *Multivariate Behavioral Research*, Vol. 43 No. 2, pp. 289-326.

Howard, P.E.N., Painie, L. and Jones, S. (2001), "Days and nights on the internet: the impact of a diffusing technology", *American Behavioral Scientist*, Vol. 45 No. 3, pp. 382-404.

Katz, J.E., Rice, R.E. and Aspden, P. (2001), "The internet, 1995-2000: access, civic involvement, and social interaction", *American Behavioral Scientist*, Vol. 45 No. 3, pp. 404-19.

Kiyici, F.B. (2010), "The definitions and preferences of science teacher candidates concerning Web 2.0 tools: a phenomenological research study", *The Turkish Online Journal of Educational Technology*, Vol. 9 No. 2, pp. 185-95.

Korupp, S. and Szydlik, M. (2005), "Causes and trends of the digital divide", *European Sociological Review*, Vol. 21 No. 4, pp. 409-22.

Livingstone, S. and Helsper, E. (2007), "Gradations in digital inclusion: children, young people and digital divide", *New Media & Society*, Vol. 9 No. 4, pp. 671-96.

Lohse, G.L., Bellman, S. and Johnson, E.J. (2000), "Consumer buying behavior on the internet: findings from panel data", *Journal of Interactive Marketing*, Vol. 14 No. 1, pp. 15-29.

Mills, B.F. and Whitacre, B.E. (2003), "Understanding the non-metropolitan-metropolitan digital divide", *Growth and Change*, Vol. 34 No. 2, pp. 219-43.

Miniwatts Marketing Group (2010), "Internet World Stats", available at: www.internetworldstats.com/stats.htm (accessed February 1, 2011).

Nwezeh, C.M.T. (2009), "The impact of internet use on teaching, learning and research activities in Nigerian universities: a case study of Obafemi Awolowo University", *The Electronic Library*, Vol. 28 No. 5, pp. 688-701.

Research, Development and Evaluation Commission (2009), "Digital divide in Taiwan survey", Research, Development and Evaluation Commission, Executive Yuan, Taiwan, available at: www.rdec.gov.tw/mp110.htm (accessed January 25, 2011).

Sam, H.K., Othman, A.E.A. and Nordin, Z.S. (2005), "Computer self-efficacy, computer anxiety, and attitudes toward the internet: a study among undergraduates in Unimas", *Educational Technology & Society*, Vol. 8 No. 4, pp. 205-19.

Selwyn, N., Gorard, S. and Furlong, J. (2005), "Whose internet is it anyway? Exploring adults' (non) use of the internet in everyday life", *European Journal of Communication*, Vol. 20 No. 1, pp. 5-26.

Shah, D.V., Kwak, N. and Holbert, R.L. (2001), "'Connecting' and 'disconnecting' with civic life: patterns of internet use and the production of social capital", *Political Communication*, Vol. 18 No. 2, pp. 141-62.

Teo, T.S.H. (2001), "Demographic and motivation variables associated with internet usage activities", *Internet Research: Electronic Network Applications and Policy*, Vol. 11 No. 2, pp. 125-37.

Teo, T.S.H. and Lim, V.K.G. (2000), "Gender differences in internet usage and task preferences", *Behavior & Information Technology*, Vol. 19 No. 4, pp. 283-95.

Torkzadeh, G. and Dhillon, G. (2002), "Measuring factors that influence the success of Internet commerce", *Information Systems Research*, Vol. 13 No. 2, pp. 187-204.

Vermunt, J.K. (2003), "Multilevel latent class models", *Sociological Methodology*, Vol. 33 No. 1, pp. 213-39.

Vermunt, J.K. and Magidson, J. (2005), *Latent GOLD 4.0 User's Guide*, Statistical Innovations, Inc., Belmont, MA.

Wald, A. (1943), "Tests of statistical hypotheses concerning several parameters when the number of observations is large", *Transactions of the American Mathematical Society*, Vol. 54 No. 3, pp. 426-82.

Wasserman, I.M. and Richmond-Abbott, M. (2005), "Gender and the internet: causes of variation in access, level, and scope of use", *Social Science*, Vol. 86 No. 1, pp. 252-70.

Weiser, E.B. (2001), "The functions of internet use and their social and psychological consequences", *CyberPsychology & Behavior*, Vol. 4 No. 6, pp. 723-43.

Wilson, K.R., Wallin, J.S. and Resier, C. (2003), "Social stratification and the digital divide", *Social Science Computer*, Vol. 21 No. 2, pp. 133-43.

Appendix. Composition of the regional segments

Regional segment	City/county	Individual segment S1	S2	S3	S4	Subtotal
T1	Taipei County	859	602	297	185	1,943
	Keelung City	86	58	29	16	189
	Yilan County	82	58	41	17	198
	Taoyuan County	412	290	175	90	967
	Hsinchu County	102	64	43	24	233
	Hsinchu City	89	72	27	20	208
	Miaoli County	104	77	47	27	255
	Taichung County	294	193	149	89	725
	Changhua County	219	171	125	64	579
	Nantou County	84	69	46	21	220
	Yunlin County	115	68	51	32	266
	Chiayi County	80	62	43	26	211
	Chiayi City	55	42	23	11	131
	Tainan County	170	173	96	60	499
	Tainan City	144	105	63	42	354
	Kaohsiung City	301	229	130	100	760
	Kaohsiung County	200	163	96	72	531
	Pingtung County	133	90	80	61	364
	Penghu County	17	9	5	4	35
	Hualien County	69	49	28	13	159
	Taitung County	45	28	17	14	104
	Kinmen County	17	14	6	3	40
	Leinchiang County	5	3	1	1	10
T2	Taipei City	651	460	127	117	1,355
	Taichung City	264	185	73	51	573
Total		4,597	3,334	1,818	1,160	10,909

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

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