DO ONLINE LEARNING PATTERNS EXHIBIT REGIONAL AND DEMOGRAPHIC DIFFERENCES?

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ABSTRACT
This paper used a multi-level latent class model to evaluate whether online learning patterns exhibit regional differences and demographics. This study discovered that the Internet learning pattern consists of five segments, and the region of Taiwan is divided into two segments and further found that both the user and the regional segments are highly interpretable. The individual segments are dictated by demographic variables, such as age and gender. For instance, younger people were good at employing Internet services; those 21-30 years old adopted e-learning, browsed blogs, and enjoyed the Internet more than others; and females preferred e-learning applications more than males did. On the other hand, the regional segments are dictated by the individual segments. For instance, the service area segment comprised a higher proportion of members who were good at online learning applications. The agricultural area segment made up a higher proportion of members who were traditional users. The findings provide both product or service providers/vendors and curriculum designers with an applicable guideline for developing service strategies for better matches and higher service satisfaction between the curriculum and the users' needs.
Keywords: regional difference, demographic differences, online learning pattern

INTRODUCTION

What kinds of online learning patterns do people have when they use the Internet? Understanding online learning behaviors might be helpful for increasing fitness and service satisfaction between a curriculum and students' needs. People's daily activities have gradually shifted from concrete circumstances into virtual ones. For example, bulletin boards have evolved into websites, diaries have transformed into blogs or micro-blogs, while the learning environment has migrated from actual classrooms into online ones. The rise of the Internet has extended/prolonged the service hours/time to 24 hours a day and has attracted user from all around the world. Such changes have made service-providers value users' needs and their usage behaviors on the Internet more than before. Teachers are now also more eager to perform web-reinforced teaching, and they are expected to use blogs, Wikipedia, and social network sites in their own teaching (Kiyici, 2010). It could be agreed that people are not doing anything particularly new – they are just doing old things in new ways and finding that some of those new ways suit their lifestyle better (Anderson & Tracey, 2001). More and more Internet users have contributed to the generation of online learning, like online movies, online games, online shopping, e-news, blogs, Wikipedia, and e-learning (Selwyn, Gorard & Furlong, 2005; Shah, Kwak & Holbert 2001). Forecasts are thus more likely to be reliable if they are based on consumers' on-line behaviors (Lohse et al., 2000). 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, Sprott, Silverman & Stem, 2000; Song, Kim, J. K. & Kim, S. H., 2001).

Understanding online behaviors can help increase fitness and service satisfaction between products and users' needs. This study looked at online interactive learning behavior patterns in particular issues related to browsing blogs and information sharing. This paper investigated the usage behaviors through nine items of categorical variables about online learning patterns among 16,133 users in 25 regions of Taiwan. This study implemented a multilevel latent class model to investigate online learning patterns, which exhibited regional differences and demographic difference, with the goal of providing service providers an understanding and mastery of their target users.

Typical online activities

Internet applications and services have certainly enriched peoples' lives (Anderson & Tracey, 2001; Colley & Maltby, 2008). The research results of Weiser (2001) showed that Internet usage is motivated principally by goods and information acquisition. What are typical online activities? According to research on Internet usage patterns in the U.S. from some scholars, like Howard, the chief purpose can be sorted into communication, fun, information utility, major life activities, and transactions (Howard, Painie & Jones, 2001). Some studies have shown that other activities conducted through the Internet encompass online communication, e-mail, downloading of software and games, obtaining information, shopping, researching products and service information, entertainment, and education (Sahin, Balta & Ercan, 2010; Sam, Othman & Nordin, 2005). Colley and Maltby (2008) revealed that the most common applications are communicating with friends, browsing news, acquiring general information, entertainment, shopping, and job-search information. Gross and Leslie (2009) exhibited that the new approach applications are blogs, RSS, image hosting, podcasting, social networking, and Wikipedia. In the Internet world, blog application, information sharing, and connecting to the Internet through mobile device are new issues. This study herein categorized some on-line behaviors that frequently occur and chose nine of them to analyze. These nine behaviors encompassed: purposes of entertainment, such as traveling, food, and recreation; acquiring general information; searching for product information; online shopping; searching for job information; e-learning; browsing blogs; information sharing, such as videos and photos; and connection with the Internet through a mobile phone.

Regional and demographic effects

The diffusion of the Internet has occurred at the intersection of both international and within-country differences in socioeconomics (Chen & Wellman, 2004; Donnermeyer & Hollifield, 2003). Divergent regions have different infrastructures, economies, and populations, leading to environmental divergences of location (Delialioglu, Cakir, Bichelmeyer, Dennis & Duffy, 2010; Mills & Whitacre, 2003). Hence, this also has affected divergences of citizens' Internet usage patterns (Wilson, Wallin & Resier, 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 their environments, so that they can accurately compare the on-line behaviors of users from different regions.

In addition to location, other factors that influence on-line behaviors, such as users' social status, age, and gender, are also noted as the major concerns in several research studies (Aypay, 2010; Wilson et al., 2003). For example, Livingstone and Helsper (2007) showed that demographic, use, and expertise variables all played a role in accounting for variations in the breadth and depth of Internet usage. Among them, demographic variables such as gender, age, and socioeconomic status had significant influences (Delialioglu et al., 2010; Korupp & Szydlik, 2005; Wasserman & 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). Students' characteristics (gender and weekly hours of Internet use) showed a significant relationship with their participation level in discussion forums of online courses (Yukelturk, 2010). Hargittai and Hinnant (2008) suggested that user attributes also revealed 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 on-line use patterns, like time spent over one day for browsing or downloading. The findings of Yang, Hsu, and Tan (2010) presented that the perceived ease of use is an important determinant for sharing videos (e.g. YouTube), and that social factors (e.g. gender) affect intention. Males, regardless of race, were the most intense videogame players, while females were the most intense users of cell phones (Jackson et al., 2008). Colley and Maltby (2008) showed that more women's responses mentioned receiving information and advice, studying online, and shopping and booking travel online, while more men's responses noted the Internet had helped or brought them a career and had positive socio-political effects. Lo´pez-Bonilla, J. M., and Lo´pez-Bonilla, L. M. (2010) discovered that gender has significant impacts on online shopping. This study herein referred to the findings from the scholars mentioned above and brought some demographic variables such as age and gender into the research model to analyze how these demographic variables influence the pattern of online learning.

Investigating user behavior patterns

Some scholars also indicated that understanding customer behaviors on the Internet is helpful for products' research and development, together with their sales (Lohse, Bellman & Johnson, 2000). Scholars have discovered differences among time, frequency, and the range of Internet usage (Howard et al., 2001; Selwyn et al., 2005). Changchien, Lee and Hsu (2004) presented that due to the diversity in individual usage behaviors, cognitive needs, and personality, further research of methods on clustering users may be quite interesting and helpful. Some studies suggested sorting online use pattern by users' age (Shah et al. 2001), while others explored the length of experience, access time, and frequency of online use patterns (Donnermeyer & Hollifield, 2003; Howard et al., 2001)

Another way to examine which people conduct what type of online activities is to explore user typologies. For example, researchers used factor analysis to investigate the online motivated patterns among various users (Teo, 2001; Torkzadeh & Dhillon, 2002). In online behavior studies, the behaviors of users usually showed categorical outcomes and a latent usage pattern. Although the length of experience and frequency of online use helps predict which activities people conduct online, the patterns of online behavior also prove to be a significant predictor. This study aimed to test this particular relationship of types of online usages. This study took the methodology from previous scholars and applied multilevel latent class analysis to investigate user behavior patterns based on multilevel data structures (Bijmolt et al., 2004; Henry & Muthén, 2010; Horn et al., 2008).

This research used MLCA (Multi-level Latent Class Analysis) to discover patterns of online learning. It consisted of regional areas simultaneously and also considered demographic variables such as age and gender, discussing the potential influence behind users' on-line behaviors, with the goal of providing curriculum designers an understanding and mastery of their target customers. Curriculum designers and service-providers could refer to the patterns of online learning for their own research and development. Together with their promotion of them, this might be helpful to increase/elevate fitness/appropriateness and service satisfaction between service and users' needs.

METHOD

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

Objectives of this study

Do online learning behaviors exhibit certain identifiable patterns (based on multilevel data structures)?
Do online learning patterns exhibit regional differences?
How do demographic variables affect online learning patterns?
What kind of special or interesting online learning pattern differences exist?

Multi-level latent class analysis (MLCA)

In the social sciences, many research questions have investigated the relationship when both categorical outcomes and predictor variables are latent. Categorical data analysis has been useful in looking at sociological data (Goodman, 2007). For an attitude or classify survey, researchers generally are 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 classify survey it is more appropriate to use Latent Class Analysis (Bijmolt, Paas & Vermunt, 2004; Horn, Fagan & Jaki, 2008). A latent class model assumes that the population of subjects is divided into a few exclusive latent classes. LCA (latent class analysis) is a statistical method used to identify subtypes of related cases using a set of categorical and/or continuous observed variables. These subtypes are referred to as latent classes. The classes are inferred from the multiple observed indicators and are not directly observed (Bijmolt et al., 2004; Henry & 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 the framework of a latent class analysis 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, Vermunt (2003) presented a framework for assessing latent class models with nested data. Multi-Latent class analysis (MLCA) has been suggested as a model-based tool for both regular individual (level 1) segmentation and regional segmentation (level 2) (Bijmolt et al., 2004; Henry & Muthén, 2010; Horn et al., 2008; Vermunt, 2003). This study simultaneously applied MLCA to attain regional segmentation and cross-region user segmentation. The parameters of the MLCA model can be estimated by maximum likelihood. The maximization of the likelihood function can be achieved by an adapted version of the Expectation-Maximization (EM) algorithm (Bijmolt et al., 2004; Vermunt, 2003).

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 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 herein weighted each observation by sample size according to the population of gender, age, and the population of each region. This investigation examined the extent to which there were cross-regional versus 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. Estimations are obtained for fixed numbers of regional segments (T) and user segments (S). Appropriate values for these numbers can be determined by estimating the multi-level latent class model for different values of T and S, and by examining the relative fit of alternative model specifications, e.g. by using the minimum Bayesian information criterion (BIC) rule (Henry & Muthén, 2010; Horn et al., 2008; Vermunt, 2003). A variety of studies and articles suggested the use of the BIC as a good indicator for class enumeration over the others (Henry & Muthén, 2010; Horn et al., 2008; Nylund, Asparouhov & Muthén, 2007; Vermunt, 2003).

Sample

Taiwan's Internet prevalence is rather high. In 2009 the average percentage of household Internet access was 78.1%, with average time spent on the Internet at 2.95 hours per day (Research, Development and Evaluation Commission, RDEC, Taiwan, 2009), proving that Taiwan can move side by side with developed countries in this regards, such as the United States of America (77.3%), Austria (74.8%), France (68.9%), Germany (79.1%), Turkey (45%), Japan (78.2%), South Korea (81.1%), and Singapore (77.8%) (Miniwatts Marketing Group, Internet World Stats, 2010). Therefore, the surveyed data of Internet e-learning on Taiwanese residents could be a reference to some extent and also be a good source for curriculum designers to work on e-learning products and marketing services. The collected data herein for all analyses adopted the digital divide survey conducted by the RDEC, which had intended to evaluate the status of information infrastructure implementation and the current situation in Taiwan. This annual survey of the digital divide included three parts: information and communications technology environment, skills to use the Internet, and usage behaviors of the Internet. The survey was conducted by computer and telephone interviews from July to August in 2009. Random sampling interviews were used to interview a segmented population of interviewees at age 12 or above in 25 counties and cities. The survey collected 16,133 valid random samples with a response rate of 66.4%, and the sampling errors never exceeded ±4%. This study took nine items of categorical variables about online use behavior as a research dataset. The data were used in exclusion of missing values for the 10,909 valid samples.

Nine categorical indicators were used to inform latent class membership: (1) using for entertainment purposes (1=yes, 0=no), (2) acquiring general information (1=yes, 0=no), (3) searching for product information (1=yes, 0=no), (4) using online shopping (1=yes, 0=no), (5) searching for job information (1=yes, 0=no), (6) e-learning (1=yes, 0=no), (7) browsing blogs (1=yes, 0=no), (8) sharing information (1=yes, 0=no), and (9) connection with Internet through a mobile phone (1=yes, 0=no). 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 make up level 1 of the hierarchy and regions are level 2. This study took both individual and contextual level predictors of the Internet use behaviors' typologies. Table 1 shows descriptive statistics for the Internet use sample.

Table 1: Descriptive statistics for the online behavior sample

Region	Sample size	%
Taipei City	1856	11.51
Taipei County	2712	16.81
Keelung City	274	1.70
Ilan County	322	1.99
Taoyuan County	1337	8.29
Hsinchu County	338	2.10
Hsinchu City	274	1.70
Miaoli County	387	2.40
Taichung County	1082	6.70
Taichung City	742	4.60
Changhua County	918	5.69
Nantou County	371	2.30
Yunlin County	499	3.10
Chiayi County	387	2.40
Chiayi City	193	1.20
Tainan County	789	4.89
Tainan City	532	3.30
Kaohsiung City	1077	6.68
Kaohsiung County	868	5.38
Pingtung County	627	3.89

Penghu County	64	0.40
Hualien County	241	1.50
Taitung county	161	1.00
Kinmen County	65	0.40
Lienchiang County	16	0.10
Total	16133	100.00
Demographic	**%**	
Age		
20 and younger	20.80	
21-30	25.86	
31-40	23.94	
41-50	18.51	
51 and older	10.88	
Gender		
Female	48.31	
Male	51.69	
Learning behavior	**% (had experience)**	
Entertainment	75.14	
General information	87.99	
Product information	68.52	
Online shopping	59.28	
Job information	78.33	
e-Learning	30.41	
Browser blog	76.70	
Share information (video, photo)	38.55	
Connect Internet w/mobile phone	20.31	

Model Fit

In order to study the similarities and differences between the patterns of on-line behaviors from nine Internet applications among 10,909 users and 25 regions, this study applied the multi-level latent class analysis model described beforehand. This paper incorporated the effects of two demographic variables (age and gender) by means of concomitant variables. Model estimates were obtained for alternative numbers of user segments (S=1...5) and regional segments (T=1...2). Table 2 reports model fit (in particular, the BIC value) for each combination of S and T. The minimum BIC was applied on the optimal number of user segments (Henry & Muthén, 2010; Horn et al., 2008; Vermunt, 2003). The overall minimum BIC was attained at five user segments and two regional segments (BIC= 100226), which this study identified as the most appropriate solution. The research also checked the reports' model fit through the result of the Wald test (Wald, 1943). The Wald value of the Model for Clusters (T1=52.27, p-value<0.00; T2=24.73, p-value<0.00) means the contextual level is divided into two segments with significant differences (Agresti, 2007; Wald, 1943). In addition, Models for Indicators (nine categorical indicators in level 1) are also significantly different (p-value<0.00). The covariates' variables (two demographics variables) are also significantly different (p-value<0.00). Therefore, this study divided the user level into five segments and regional level into two segments, which altogether induced the most appropriate solution thereof.

Table 2. Model fit (BIC) for alternative numbers of region and user segments

BIC	**Number of regional segments**		
Number of user segments	1	2	3
1	*110876*	110886	110895
2	*101939*	101943	101959
3	101100	*101095*	101119
4	100305	*100281*	100308
5	**100233**	***<u>100226</u>***	**100261**
6	100255	*100244*	100298
7	100289	*100280*	100325

Note: The lowest BIC within each row is in italic and within each column in boldface. The lowest BIC overall is underlined.

RESULTS

User and regional segmentation

Do online learning behaviors exhibit certain identifiable patterns (based on multilevel data structures)? Table 3 presents Internet use and online learning behaviors within each user segment. The table shows the conditional probabilities of nine users' online behaviors. At the individual level, this paper discovered that the Internet use pattern consists of five segments (S1-S5) that showed distinctive online learning patterns. Taiwan was divided into two regional segments (referred to as T1 to T2), where Figure 1 presents each regional segment, and the population size of each group is 53.33% and 46.67%. In order to deduce interpretation, this paper offered regional segment membership probability through the category of each user segment, averaged across all categories (user segment) of the other regional segments. Based on individual level (five segments) and contextual level (two segments), this paper summarized the multi-contingency by a table of regional segments and administrative region of Taiwan (see Appendix A). Regional Segment 1 (T1) includes relatively more metropolitan areas, and most of the local governments focus on service development. This class was categorized as the service area segment. Regional Segment 2 (T2) locations are in central or southern Taiwan which encompasses mainly agricultural areas. This class was categorized as the agricultural area segment. These two regional segments of the composition are different.

Users' on-line behaviors and thereby membership of user segments are often related to demographic variables such as age and gender. This paper assessed the effects of two demographic variables: age and gender. Ages included under 20, 21-30, 31-40, 41-50, and above 51 for 5 species. The probability that a user belonged to a particular segment is modeled to depend on his/her demographics and on regional segmented membership. To assess the significance of the demographic effects, this paper employed the Wald test (Agresti, 2007; Wald, 1943) for nested models. Both two demographic variables significantly affected user segment factors: age (Wald value=1934.57, p<0.001) and gender (Wald value=63.83, p<0.001). The lower part of Table 3 presents the findings for the effects of demographic variables. In order to deduce further interpretation, this paper referred to the practice by Bijmolt et al. (2004) and did not present logic parameters, but rather segmented membership probability per category of each demographic variable, averaged across all categories of the other variables. For example, the rate of males in every user segment (S1 to S5) was 32%, 30%, 14%, 16%, and 9%, respectively.

Table 3. Model Results: User Segments

	Individual (user) segment							Regional segment	
	S1	S2	S3	S4	S5	likelihood ratio chi-square test		likelihood ratio chi-square test	
Cluster size	**0.33**	**0.31**	**0.15**	**0.14**	**0.06**	χ^2	p-value	χ^2	p-value
On-line behaviors	**Behaviors probabilities**								
Entertainment	0.64	0.95	0.33	0.96	0.88	3404.17	0.00	1.01	0.31
General information	0.95	0.98	0.67	0.88	0.49	1982.52	0.00	46.95	0.00
Product information	0.83	0.96	0.23	0.46	0.10	5523.59	0.00	76.64	0.00
Online shopping	0.67	0.95	0.19	0.26	0.09	5861.55	0.00	41.69	0.00
Job information	0.80	0.96	0.36	0.89	0.55	2733.33	0.00	1.56	0.21
e-Learning	0.24	0.48	0.06	0.37	0.16	1366.99	0.00	0.51	0.47
Browsing blogs	0.74	0.99	0.27	0.97	0.48	4678.31	0.00	7.89	0.00
Information sharing (videos, photos)	0.14	0.76	0.04	0.62	0.08	5519.50	0.00	1.69	0.19
Connection to the Internet through mobile phone	0.15	0.36	0.06	0.17	0.10	941.35	0.00	14.26	0.00
Demographics variables	**Relative sizes of individual segment**								
Age						9890.28	0.00	49.75	0.00
20 and younger	0.00	0.25	0.00	0.55	0.20				
21-30	0.22	0.60	0.06	0.08	0.04				
31-40	0.53	0.33	0.11	0.01	0.03				
41-50	0.57	0.13	0.29	0.01	0.01				
51 and older	0.39	0.04	0.52	0.05	0.00				
Gender						162.37	0.00	1.46	0.23
Female	0.34	0.33	0.16	0.13	0.03				
Male	0.32	0.30	0.14	0.16	0.09				

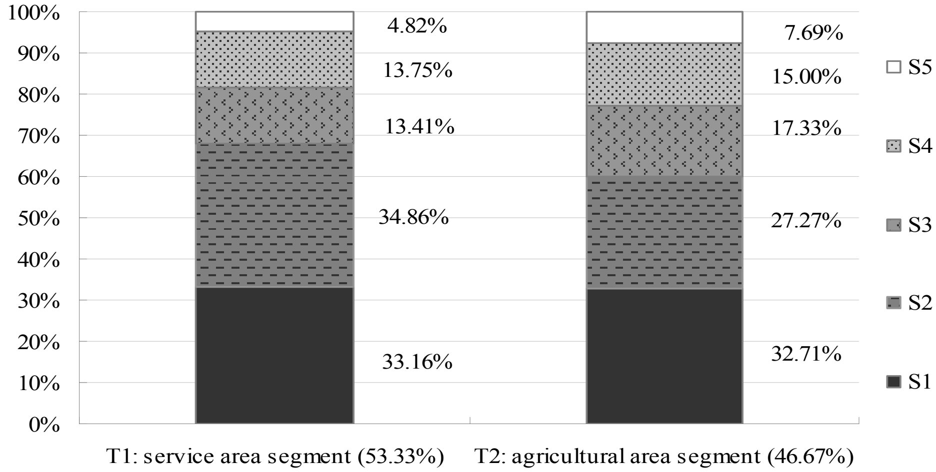

Figure 1. Multilevel latent class solution

Full model estimated

Do online learning patterns exhibit regional differences? This paper further assessed the significance of the individual segment effects. Moreover, the individual segment (user segment) variables significantly affected regional segment membership (χ^2=93.27; df=4; p-value<0.00). These results show that online learning patterns did exhibit regional and demographic differences and that the online behavior patterns exhibited urban and rural differences. For instance, the service area segment comprised a higher proportion of members who were good at using the Internet. The agricultural area segment made up a higher proportion of members who occasionally used the Internet. These two regional segments of the composition were different.

How do demographic variables affect online learning patterns? The full model is next estimated, including both two concomitant variables. To assess the significance of the demographic effects, this research employed the likelihood ratio test for nested models. All two demographic variables significantly affected user segment membership: age (χ^2=9890.27; df=16; p-value<0.00) and gender (χ^2=162.37; df=4; p-value <0.000). Users' personal characteristics dictated the individual segments. Age and gender had a large influence on the user segment probabilities. For instance, younger people were good at various online services, as they conducted more interactive applications than others. Older people were less likely to use online learning applications. Of the users' personal characteristics included in this study, gender had the smallest impact, as shown by the chi-square test values and the differences between the segment membership's probabilities (right part of Table 3). Generally speaking, males were relatively energetic at connecting to the Internet through a mobile phone, while females had a comparative concern for online shopping.

Online users' behavior patterns

This study took the contextual effect influenced by areas and their demographic variation into account for analysis. Table 3 shows the conditional probabilities of each of the nine types of use behavior within each individual segment (S1-S5, level 1). By considering some demographic variables such as age and gender, this paper divided user segmentation at the individual level into five 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-S5 and T1-T2) effectively partitioned the online learning pattern among 10,909 users. User segmentation in each model of users' on-line behaviors was not the same. Figure 1 and Table 3 summarize a more detailed classification of users' on-line behaviors. Considering contextual level (regional) and demographic variables, the five patterns of users' on-line behaviors (user segments S1 to S5) are stated as follows.

S1: This segment consisted of 33% of the total samples, chiefly composed of ages 31-50. They were good at using the Internet for information research related to work and business communication, such as researching general information (95%), searching for product information (83%), and searching for job information (80%). They had relatively lower frequencies to use it for entertainment (64%) and information sharing (14%). Their contextual level resided evenly in each regional segment. This group was categorized as the business segment.

S2: This segment consisted of 31% of the total samples. This group was knowledgeable on various Internet applications, such as entertainment (95%), researching general information (98%), searching for product information (96%), online shopping (95%), searching for job information (96%), and browsing blogs (99%).

Within this group, 76% have experienced sharing information (video, photo), 48% of them have used e-learning, and their connection to the Internet through a mobile phone was even up to 36%: these are the highest conditional probabilities of all segments. Their contextual level (regional segment) had a maximum number in the service area segment. This group was categorized as the knowledge segment.

S3: This segment consisted of 15% of the total samples. They were not young. They used traditional Internet applications such as researching general information (67%) and searching for product information (23%). Only 19% of them used online shopping and less than 10% of them used e-learning, sharing information, and connecting to the Internet through a mobile phone. Their contextual level (regional segment) had more numbers in the agricultural area segment. This group was categorized as the traditional segment.

S4: This segment consisted of 14% of the total samples. They basically were composed of people under the age of 20. More than 85% of them used the Internet for entertainment, general information, job information, and browsing blogs. Their use of e-learning, frequencies, and participation of information sharing was relatively high (37% and 62%), whereas their connection to the Internet through a mobile phone was also significantly prominent (17%). Their contextual level resided evenly in each regional segment. This group was categorized as the active segment.

S5: This segment consisted of 6% of the total samples. Most of them were young and skilled in using amusement services such as for entertainment (88%) and browsing blogs (48%). They did not to care about product information (10%), information sharing (8%), or e-learning (16%). They rarely used online shopping (9%), but they did use the Internet for researching general information (49%). This group had a higher proportion of males. Their contextual level (regional segment) had more numbers in the agricultural area segment. This group was categorized as the entertainment segment.

What kind of special or interesting online learning pattern differences exist? These five user segments showed distinctive online behavior patterns. The knowledge segment's members were good at various Internet applications. Most of the knowledgeable users were relatively energetic for online learning versus the others, and websites could offer these users discounts of customization to attract their use. The active segment's members were relatively young and skilled at various online interactive applications, such as browsing blogs, online sharing information, and e-learning. If a service designer is trying to target this group, then it could use pre-introduction or a trial together with a promotion of an online interactive service. The business segment's members had relatively lower frequencies to use the Internet for entertainment and information sharing. If a service designer is trying to target the business segment, then it should enhance work and business communication services. The entertainment segment's members preferred to use the Internet for entertainment and were inexperienced at online shopping service. The traditional segment's members were not young and had a lower use rate of online services, whereas they also used general information searching service. If a service designer is trying to target the traditional segment or the entertainment segment, then it should offer these users a relative friendly and easy-to-use service to attract their purchases.

CONCLUSIONS

This study has applied nine types of online applications as the classification scheme from the survey of the digital divide conducted by RDEC in Taiwan in 2009. This study used a multi-level latent class model to evaluate whether the online learning patterns exhibited regional differences in Taiwan at both the individual level and the regional level. This paper categorized the online leaning patterns into five user segments: business, knowledge, traditional, trendy, and entertainment. At level 2, this paper categorized the population into two regional segments: service area and agricultural area. This paper found that both user segments and regional segments were highly interpretable. Do online learning patterns exhibit regional and demographic differences? Yes, they do.

MANAGERIAL IMPLICATIONS

The regional segments are dictated by the user segments (level 1). For instance, the service area comprised a higher proportion of knowledge segments and business segments (level 1). This service area group was made up of a higher proportion of members who were good at using online learning applications, such as acquiring general information, searching for product information, and browsing blogs. The agricultural area comprised a higher proportion of the traditional segment and entertainment segment (level 1). This agricultural area group made up a higher proportion of members who used the Internet for entertainment applications and a lower proportion of people who were good at using the Internet.

The results of the analysis indicated that age and gender influenced online learning behaviors. For instance, younger people were good at using Internet services, as those aged under 30 adopted entertainment, online shopping, and connecting to the Internet through a mobile phone more/faster than others. Younger people preferred interactive applications such as e-learning, browsing blogs, and sharing information, while older people used traditional Internet services, such as general information research. The gender difference affected online usage patterns. This research showed that males preferred enjoyment applications, such as entertainment service, while females preferred education or purchasing Internet services, such as e-learning or online shopping.

This paper has suggested that Internet product or service providers could find more appropriate user clusters based on the characteristics of products. Partnerships between users' demographic and regional institutions should prove valuable for service area population and agricultural area population segments by enabling online learning applications. 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, online shopping, e-learning, blog, or mobile phone service. People aged 21-30 were the major users of online learning applications, and websites could offer these users appropriate interactive functions and discounts of customization to attract their purchases. E-learning or online shopping websites could offer females an appropriate discount of customization to attract their purchases.

Among individual segment members using the Internet to look for general information, searching for product information, online shopping, browsing blogs, and using a mobile phone connection to the Internet had the most obvious differences between service area and agricultural area. Service providers can offer an appropriate collocation of local product information, customized interaction blogs, and a trial together with promotions on online learning applications in order to attract such usage. On the other hand, websites could offer knowledge segment members a mobile learning service and discounts of customization to attract their use. Service designers could use pre-introduction or a trial together with a promotion on an online interactive service to invite active segment members' use. Websites could make themselves more applicable to business segment members by enhancing work and business communication services. 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 online learning patterns for their own online curriculum design, which might be helpful to increase the fit and service satisfaction between products and users' needs.

LIMITATIONS AND FUTURE RESEARCH

The multi-level latent class results herein described the current usage segmentation structure based on online learning patterns, without making inferences on what may have caused these patterns. In general, the online learning behavior by a user will not only depend on the user's skills and needs, but will also partly be driven by what education department is offered. It remains unclear to what extent demand or supply factors have generated the online learning patterns observed in this paper. For a conclusion on this topic, further research could investigate the influence of the curriculum offerings and other service efforts by education department on user behavior-portfolios in different regions. On the other hand, one limitation of the database concerns the lack of information on cross-regional equivalence, such as local economic capacity. The performance of the multi-level latent class model will depend on the number of countries or the number of users per region. Future research using a larger and broader set of regions could highlight the value of simultaneously grouping regions and users.

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Appendix

Appendix A. The region composition of the Regional Segment

City/County	Regional Segment T1	Regional Segment T2	Subtotal
Taipei City	1355	0	1355
Taipei County	1942	0	1942
Keelung City	189	0	189
Ilan County	198	0	198
Taoyuan County	967	0	967
Hsinchu County	233	0	233
Hsinchu City	208	0	208
Miaoli County	0	256	256
Taichung County	0	726	726
Taichung City	572	0	572
Changhua County	0	579	579
Nantou County	220	0	220
Yunlin County	0	265	265
Chiayi County	0	211	211
Chiayi City	131	0	131
Tainan County	0	499	499
Tainan City	0	353	353
Kaohsiung City	0	760	760
Kaohsiung County	0	532	532
Pingtung County	0	364	364
Penghu County	36	0	36
Hualien County	158	0	158
Taitung county	104	0	104
Kinmen County	40	0	40
Lienchiang County	11	0	11
Total	6364	4545	10909