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A Study on Finding out Barriers of Diffusion of Social Media - Assisted Learning: Focusing on the perception of learners Using Latent Class Analysis

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Abstract

Despite the increased use of social media for teaching and learning in Korea, there is very little literature on the barriers that learners perceive in social media assisted learning. Based on this situation, the following research questions were addressed: a) Is it possible to classify Korean undergraduate students into groups according to barrier to using social media on learning? If so, are there underlying types of these barriers? b) are gender and digital literacy predictive of membership in types of barriers? For this research, data was gathered from 756 Korean undergraduate students, and I carried out latent class analysis (LCA) and multinominal logistic regression. For this, I used PROC LCA, SAS procedure. The results are following. Firstly, four different types identified based on the barriers. Secondly, gender (p<. 05) and information digital literacy (p<. 001) was predictors of latent class membership in types of barriers.

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Keywords: social media, barriers to use, digital literacy, latent class analysis, multinominal logistic regression;

1. Introduction

According to rapid diffusion of social media, more and more universities from all over the world are transitioning from traditional education towards Education 2.0 integrating social media such as blogging, multimedia sharing, collaborative content, and social networking. However, there is little empirical studies on what barriers

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undergraduate students perceive using social media in academic activity in Korea. Based on this situation, following research questions were addressed in this research. What are barriers when Korean university students use social media in learning? What differences, if any, exist between barriers to use? Is it possible to classify Korean undergraduate students into groups according to their barriers to use social media on learning? Secondary, are gender and digital literacy predictive of membership in types of barriers? According to research questions, the objectives of this research are to identify latent class of barrier to use social media, and to investigate whether digital literacy and gender have effect on underlying types.

2. Literature review

Barriers of technology include lack of motivation due to poor social skills, poor computer skills and a lack of availability of access; a lack of time and class time and a lack of motivation and social awareness and school culture. The major barriers of education technology include a lack of confidence, competence and a lack of access to resources (Bingimlas, 2009). Whereas information sufficiency is an important predictor of information seeking, factors such as affective response and involvement can also influence information seeking behaviour (Kuttschreuter, 2006). College students’ gender might influence their perceptions toward Web 2.0 applications in the context of learning. Although the use of social media for sharing information and engaging have been shown to have positive outcomes, there are a number of uncertainty related to credibility of both the information shared and that of the information source using social media. The issue of the credibility was key factor that may be responsible for the effective utilization of the information shared on social media (Santana & Wood, 2009). Aspects of digital media skills include technical literacy, informational literacy, and critical literacy. Technical literacy involves the operation of individual digital media. Informational literacy includes the ability to effectively retrieve, access, and utilize information. Critical literacy broadly refers to the ability to render accurate judgments about media and to recognize unstated assumptions and values. ICT self-efficacy is an individual’s belief regarding ability to utilize ICT, and plays a positive role to decisions involving ICT adoption and usage (Torkzadeh, Chang & Demirhan; 2006; Sam, Othman, & Nordin, 2005).

3. Research Design

3.1 Data Collecting Methods and Participants

The study was conducted at the Daegu University and Kyungpook National University, Korea. Data were collected through an online survey during September, 2013 by means of questionnaires. The response rate was 85.7% with a total of 987. Some participants’ datasets were removed due to incompleteness or errors. The total sample consisted of 756 participants (37.4% male, 62.6% female; 20.7% freshmen, 23.8% sophomore, 24.0% juniors, 31.4% seniors; 6.6% non possession of smart phone, 93.4% possession of smart phone).

3.2 Instruments

Questionnaire have been created via making a literature review and designating definitions and common issues related to the subject. Furthermore, some expert views were taken in order to extend the internal reliability and validity of study findings. The survey instruments contained three sections: demographic information, digital literacy, and barrier to using social media. Demographic and descriptive information on survey participants was collected, including variables such as gender, possession of smart phone, year, major, professor’ pressure on using in the course. Digital literacy questionnaire items were constructed in order to measure a student’s perceived ability to perform tasks relevant to social media.

By principal components factor analysis with a varimax rotation, three factors (information digital literacy; technical digital literacy; critical digital literacy) were yielded. Coefficients of reliability for all subscales were satisfactory (information digital literacy .88; technical digital literacy .82; critical digital literacy .73). A set of 12 statements measuring barriers (incredibility, cost, poor social skills, lack of English skill, poor ICT efficacy, copyright, negative image because associated with advertisement, extreme opinions, bullying, an overload of
information, competition of traditional media, invasion of privacy, limited knowledge, and personal limited knowledge of applications) were asked to respondents, allowing as many possible answers as they considered appropriate. The scale used was 1 = do not agree, 2 = agree.

3.3 Statistical Analysis

Statistical analyses were done with the software program SPSS 20.0 (SPSS Inc., Chicago, IL, USA). Based on the research question, data analysis of this study consisted of descriptive and inferential statistical analyses upon removing incomplete responses. The descriptive statistics was used to analyze use frequency of social media among participants. The second phase of the analysis was to identify latent class of barriers to use social media in learning. The third phase of the analysis was performed multinominal logistic regression analysis to further investigate difference in regard of gender and digital literacy.

4. Result findings

4.1 Are there underlying types of barriers to use social media in learning?

To identify whether there a latent class structure that adequately represents the heterogeneity in barriers to use social media in learning, I carried out latent classes. Entropy values, the AIC and ABIC can be used to compare models with different numbers of latent classes. Entropy values over 0.8 indicate a good separate of the latent classes(Celeux, G., & Soromenho, G., 1996). A smaller AIC and BIC for a particular model suggests that the trade-off between fit and parsimony is preferable. With technical value, model interpretability should be considered. For example, each class should be distinguishable from the others on the basis of the item-response probabilities, no class should be trivial in size, and it should be possible to assign a meaningful label to each class(Lanza, S. T., et al., 2007). As Table 2 shows, based on the AIC value, ABIC value, and Entropy value, four classes and five classes fit. But considering model interpretability, four-class model is better than five-class model. An inspection of the parameter estimates from the four-class model suggests that the classes are distinguishable and nontrivial, and meaningful labels can be assigned to each.

Table 1. Comparison of Baseline Models

<table>
<thead>
<tr>
<th>class no.</th>
<th>Likelihood Ratio (G^2)</th>
<th>df</th>
<th>Entropy</th>
<th>AIC</th>
<th>ABIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>1763.25</td>
<td>32736</td>
<td>0.65</td>
<td>1825.25</td>
<td>1852.20</td>
</tr>
<tr>
<td>3</td>
<td>1600.64</td>
<td>32720</td>
<td>0.76</td>
<td>1694.64</td>
<td>1735.50</td>
</tr>
<tr>
<td>4</td>
<td>1546.84</td>
<td>32704</td>
<td>0.80</td>
<td>1672.84</td>
<td>1727.60</td>
</tr>
<tr>
<td>5</td>
<td>1494.50</td>
<td>32688</td>
<td>0.81</td>
<td>1652.50</td>
<td>1721.17</td>
</tr>
<tr>
<td>6</td>
<td>1448.16</td>
<td>32672</td>
<td>0.76</td>
<td>1638.16</td>
<td>1720.75</td>
</tr>
</tbody>
</table>

Note. Boldface type indicates the selected model. AIC = Akaike's Information Criterion; ABIC = Adjusted Bayesian Information Criterion.

Each column of Table 2 shows, for each class, the assigned label and probability of membership, as well as the item-response probabilities for endorsing each item.

In this research, the respondents were grouped into four latent class: 'the untrustworthy', 'technology muddlers', 'fearful users', and 'don't-care'. 58.72% of respondents are expected to belong to the untrustworthy' class. Also, 19.71% are expected to belong to the 'fearful users' class. The remaining classes are 'technology muddlers' (10.24%) and 'don't-care'(11.33%).

Table 2. Item-Response Probabilities for Four-Class Model: Probability of Endorsing Item Given Latent Class

| Item | Latent Class |
The untrustworthy  Technology muddlers  Fearful user  Don't-care

1. cost  0.5872  0.1024  0.1971  0.1133
2. poor social skills  0.5643  0.8676  0.7942  0.1301
3. poor searching skill  0.000  0.4778  0.3061  0.0000
4. poor English ability  0.3129  0.3241  0.6832  0.0000
5. invasion of privacy  0.8627  0.9576  0.9019  0.2228
6. copyright  0.7179  0.5962  0.8975  0.0703
7. limited knowledge of learning content  0.1482  0.0000  0.7154  0.0000
8. extreme opinions and bullying  0.8283  0.7633  0.7535  0.1636
9. an overload of no-filtered information  0.8330  0.9374  0.8916  0.1611
10. preferences for traditional websites  0.1632  0.8202  0.4562  0.1978
11. limited knowledge of applications  0.0927  0.1676  0.5470  0.0725
12. non-credibility  0.1950  0.3728  0.6013  0.1220

4.2 Are gender and digital literacy predictive of membership in types of barriers?

To testify whether gender and digital literacy are predictive of membership in types of barriers, gender and digital literacy were added as covariates. The ‘don't-care’ (Class IV) was specified as the reference class for the multinomial logistic regression.

Table 3. Parameter Estimates and Odds Ratios for Covariates

<table>
<thead>
<tr>
<th></th>
<th>class I</th>
<th>class II</th>
<th>class III</th>
<th>class IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.3335</td>
<td>3.7943</td>
<td>-0.4888</td>
<td>0.6134</td>
</tr>
<tr>
<td>gender*</td>
<td>0.2189</td>
<td>1.2448</td>
<td>0.0642</td>
<td>1.0664</td>
</tr>
<tr>
<td>information</td>
<td>0.1708</td>
<td>1.1862</td>
<td>-0.0439</td>
<td>0.9570</td>
</tr>
<tr>
<td>literacy***</td>
<td>0.0205</td>
<td>1.0207</td>
<td>-0.0169</td>
<td>0.9833</td>
</tr>
<tr>
<td>technical literacy</td>
<td>0.5246</td>
<td>1.6898</td>
<td>0.6851</td>
<td>1.9841</td>
</tr>
<tr>
<td>critical literacy</td>
<td>0.1189</td>
<td>0.1024</td>
<td>0.1971</td>
<td>0.1133</td>
</tr>
<tr>
<td>OR: Odds Ratio</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 3 shows the parameters for the effect of each covariate as well as odds ratios. As Table 3 shows, information literacy (p<.001) and gender(p<.05) was predictors of latent class membership. For gender(a dummy
variable: male, 0; female, 1), odds ratios are interpreted as the increase in odds of membership in a particular latent class relative to the reference class. For literacy (a standardized variable), odds ratios are interpreted as the increase in odds of membership in a particular latent class relative to the reference class corresponding to a one-unit increase in the covariate. The interesting finding is that female were 24% more likely to be in the untrustworthy class than the 'don't-care' class.

5. Implication and Suggestion

Based on this research, three classes except the don't care class perceived invasion of privacy as barrier. To search learning data, social media users have not to register, but users have to register in social media for producing content such as posting and commenting. Because of fear for invasion of privacy, the students can prefer to passively take pre-existing content rather than actively make their own content. To maximize potential of social media as learning assisted tool, we try to decrease barriers. The barriers of technology can only be eradicated when there is a common understanding and agreement by all stakeholders on each of the aspect. It will take time and research to validate why technology is important.

References