Jo, I. H., Kim, D., & Yoon, M. (2015). Constructing Proxy Variables to Measure Adult Learners' Time Management Strategies in LMS. *Educational Technology & Society, 18* (3), 214–225.

Constructing Proxy Variables to Measure Adult Learners' Time Management Strategies in LMS

Il-Hyun Jo[1*], Dongho Kim[2] and Meehyun Yoon[3]

[1]Department of Educational Technology, Ehwa Womans University, Seoul, Korea // [2]Department of Career and Information Studies, University of Georgia, GA, USA // [3]Department of Career and Information Studies, University of Georgia, GA, USA // ijo@ewha.ac.kr // dongho@uga.edu // meehyun@uga.edu

[*]Corresponding author

(Submitted May 5, 2014; Revised October 31, 2014; Accepted December 31, 2014)

ABSTRACT

This study describes the process of constructing proxy variables from recorded log data within a Learning Management System (LMS), which represents adult learners' time management strategies in an online course. Based on previous research, three variables of total login time, login frequency, and regularity of login interval were selected as candidates from the data set, along with a guideline for manipulating the log data. According to the results of multiple regression analysis, which was conducted to determine whether the suggested variables actually predict learning performance, (ir)regularity of the login interval was correlative with and predictive of learning performance. As indicated in the previous research, the regularity of learning is a strong indicator for explaining learners' consistent endeavors and awareness of learning. This study, which was primarily based on theoretical evidence, demonstrated the possibility of using learning analytics to address a learner's specific competence in an online learning environment. Implications for the learning analytics field seeking a pedagogical theory-driven approach are discussed.

Keywords

Learning analytics, Educational data mining, Time management strategy, Adult education

Introduction

There are high demands within e-learning for adult learners. Over the past years, there has been an increase in online course enrollment among adult learners in order to obtain knowledge or develop professional skills (Cohen & Nycz, 2006; Hrastinski, 2008; Wang, Vogel, & Ran, 2011). In spite of a great deal of attention that has been paid to such online courses, learners have faced challenges when taking such online courses due to a lack of time management skills (Kwon, 2009). Time management strategies are increasingly required in the context of adult learning, because such learners are in the usual situation of being involved both in their study and their job at the same time; therefore, the successful completion of an online course depends on the efficient use of a given amount of time. Failure in online courses for adult learners has been reported to result from poor time management (Eastmond, 1998; Joo, Jang, & Lee, 2007).

To address these issues, utilizing log data of the learners can be considered. Log data reflect learners' online behaviors, which are closely related to their learning style (Hwang & Wang, 2004; Sharma & Gupta, 2012). Instructors can detect the status of their learning processes at earlier stages (Hung & Zhang, 2008; Nanjiani, Kelly, & Kelly, 2004). If they can distinguish learning patterns in the early stage of an online course, it will be conducive to encouraging or guiding learners by providing them with appropriate instructional intervention (Brown, 2011).

Log data, which is saved as an unstructured data set, contains users' log information within online systems. Users begin their studies when they log into a web page, where they stay until they complete their learning. Because the log data detects every activity and click made by the users who are taking the courses, it can be used to represent how the learning processes occur on the web throughout the login duration. Furthermore, this information might be more genuine when compared to the data obtained from surveys, which rely highly on learners' recall and subjective interpretations; thus, the possibility of distortion or low reliability need not be considered (Baker, 2010; Elias, 2011). However, log data alone cannot be transferred to meaningful learning processes without sophisticated interpretation of the theoretical aspects. The contribution of this study is to suggest an effective way to convert users' log data into predictive indicators of learning performance based on a theoretical background.

The focuses of this study were two fold. First, "candidates for proxy variables" from the log data set that represent learners' time management strategy were elicited, conceptual constructs that have long been considered to be a vital factor to high performance (Barling, Kelloway, & Cheung, 1996; Macan, Shahani, Dipboye, & Philips, 1990; Printrich, & DeGroot, 1990; Song, Singleton, Hill, & Koh, 2004; Zimmerman, 2002). Second, it was determined whether the elicited proxy variables predict learner performance in terms of verifying the empirical validity. The proxy variables identified can be used to detect the status of learners' time management and to predict performance in other data sets from similar contexts.

Proxy variables to represent time management strategy

A proxy variable refers to an alternative that can be used when the actual variable is not measurable or not reliable (Jo & Kim, 2013; Wickens, 1972). Proxy variables have been widely used in the field of social science for the generation if prediction models (Durden & Ellis, 2003). Time management strategy was decided to be a constant habit of learners that is clearly manifested in their behaviors and accurately measured through analysis of the behavioral data, rather than use of self-reporting questionnaires that can lead to significant bias.

In order to establish reliable proxy variables, we attempted to build a solid theoretical foundation, which provides the rationale for manipulating the data set.

Since previous studies took different approaches to define time management strategy, candidates for proxy variables assumed to represent time management strategy were constructed. The following steps were taken to convert the unstructured data set into proxy variables (see Figure 1).

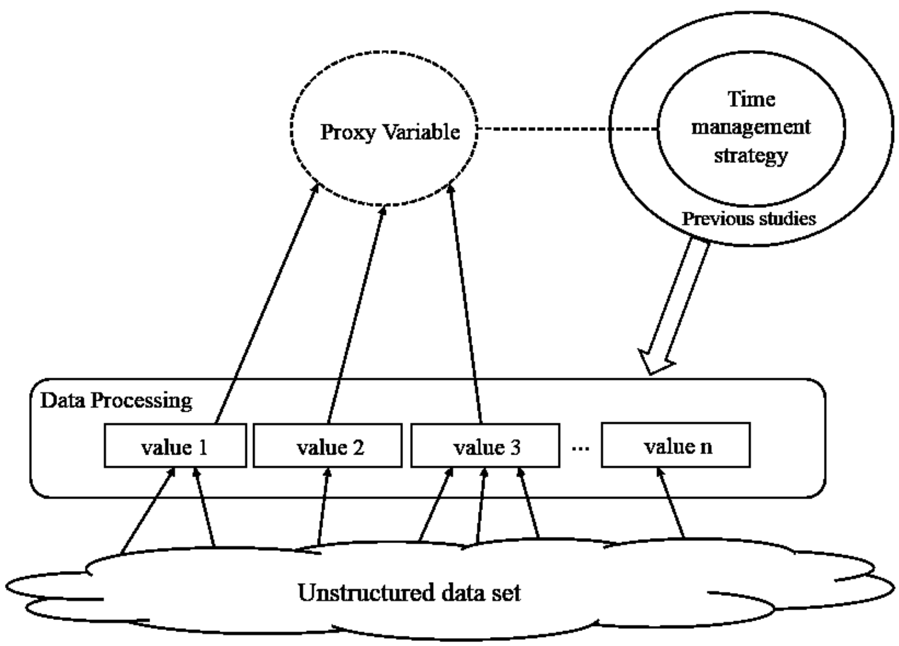

Figure 1. A conceptual framework for the construction of proxy variables

First, as a targeted conceptual construct, the concept of time management strategy was examined based on findings from previous studies. A body of literature on time management strategy of adult learners was examined, focusing on its definition, sub-factors, and impact.

The findings provided in previous research dictated the manipulation of data; further, necessary values, such as time spent on each activity and login points obtained from the data set, were extracted for further calculation. In essence, by considering the theoretical aspect, it was determined which things should be included from among the values in the data set.

A proxy variable, not identical to the targeted conceptual construct but optimally processed, can be applied to other data sets in order to determine whether learners' behaviors within the systems represents the targeted conceptual construct. In this study, three variables were chosen on the basis of previous studies.

Time management strategy

A large body of research has argued that time management strategies are deeply associated with the ability to prioritize tasks (Jex & Elacqua, 1999; Kaufman-Scarborough & Lindquist, 1999; Blaxter & Tight, 1994). With higher levels of time management ability, learners are able to better organize the given tasks in the order of importance. Because all the participants had to receive a certain required score on the final exam to complete the course, it was determined that those with a higher level of time management strategy would put more effort into the course, which would result in more commitment to learning. This assumption is in accordance with previous studies, which have regarded time management as a technique for having sufficient time to accomplish the required tasks (Slaven & Totterdell, 1993; Woolfolk & Woolfolk, 1986). Many adult learners involved in both work and study succeed to achieve their academic goals when they spend extra time only for learning outside of work (Kember, 1995; Blaxter & Tight, 1994). From the perspective that regards it as a sub-element of self-regulated learning, many researchers have also emphasized the efficient use of time (Hofer, Yu, & Pintrich, 1998; Printrich & DeGroot, 1990; Pintrich, Smith, Garcia, & McKeachie, 1993; Zimmerman, 2002). The concept incorporates a series of sub-factors, such as sufficient amount of time investment in tasks and active participation (Blaxter & Tight, 1994; Orpen, 1994; Woolfolk, & Woolfolk, 1986).

On the other hand, long-range planning has been considered to be a crucial factor for explaining time management strategy (Britton & Tesser, 1991; Eastmond, 1998). By sustaining consistent efforts based on a well-planned schedule, learners are able to maintain the expected conditions over the long-term, as well as achieve their expected learning outcome more effectively. It was assumed herein that learners who sustain consistent endeavors are more likely to study on a regular basis. That is, having constant awareness of their learning results in regular intervals among visits, because they want to keep themselves updated on new information. Regular study was considered to be the result of prioritization strategy, as it implies that the learners tried to be more engaged in their learning with consistent awareness.

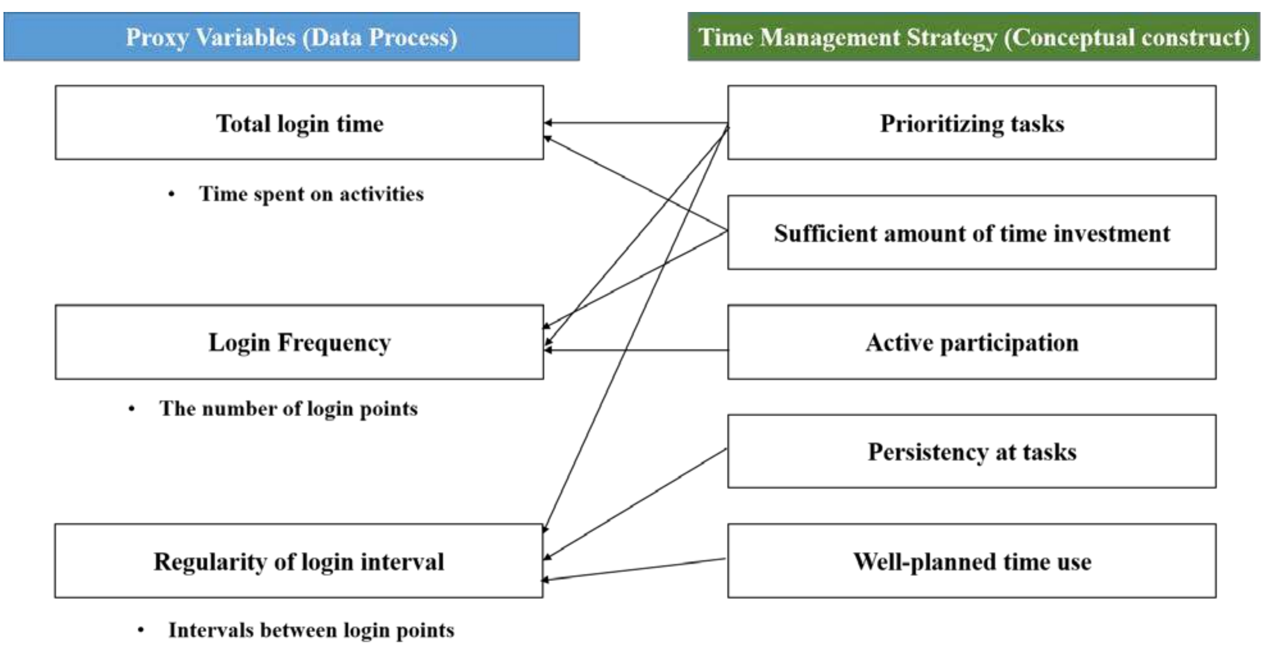

Figure 2. Selection of three variables

Based upon the theoretical evidence described above, potential proxy variables which represent time management strategy were chosen. They encompassed learners' quantified endeavors, participation and consistency throughout the time of the study. The relationship between each potential proxy variable and sub-element of the time management strategy is presented in Figure 2, as a targeted conceptual construct.

Total login time

The degree to which learners invest their time has been recognized as a factor correlative with learning performance; moreover, a great deal of research has reported a strong relationship between total studying time and performance (Beaudoin, 2002; Carroll, 1963; Hwang & Wang, 2004; Thurmond, Wambach, & Connors, 2002).

Studying time for the online course was calculated based on "login time," since the actual learning in an online course mostly occurs while being logged in. To support the significance of the variable, the conception of learning time as suggested by Cotton and Savard (1981) was adopted (see Figure 3). In the study, learning time was comprised of three parts: Allocated Time (AT), Time-on-Task (TOT) and Academic learning time (ALT). This conception is illustrated as follows.

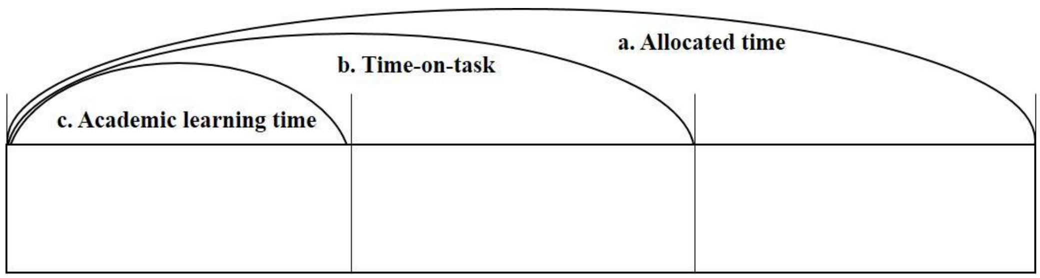

Figure 3. Three types of learning time

In the original study, the authors argued that all three types of time are correlated with learning performance. This is in accordance with subsequent studies relating time spent on learning to learning achievement (Hwang & Wang, 2004). It can be assumed that the recorded login time can be considered as learning time, as it belongs to either the allocated time or time-on-task categories. In fact, the majority of previous studies used login duration as the measurement of learning time (e.g., Hung & Zhang, 2008; Hwang & Wang, 2004). However, determination of a more reliable learning time was attempted herein by combining time spent on each activity, such as watching lectures, reading materials, or posting questions. This is a more effective way than using total login duration, since the whole duration of the login might not be fully devoted to learning. For example, login time inevitably includes simple accesses which involve no learning activity. If each activity is combined, however, time spent on actual learning activities can be obtained exclusively.

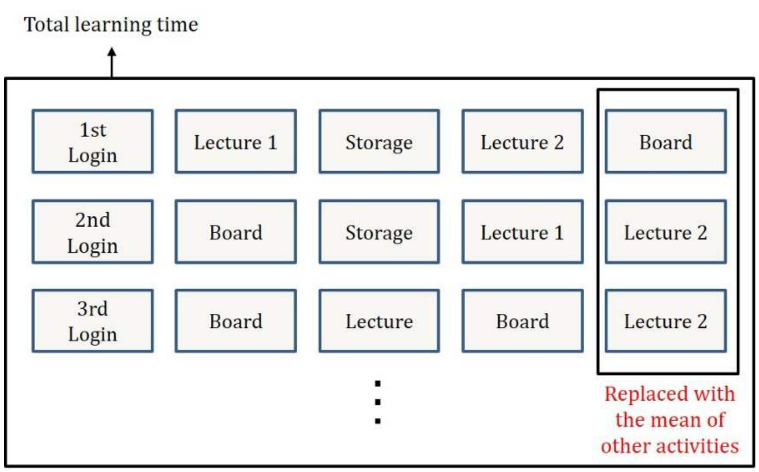

Figure 4. An example of calculating total login time

Another data processing step was taken to deal with the fact that many learners logout simply by closing their browser without actually clicking a “sign out” button, which results the logout time not being recorded in the system. The time spent on the last activity before the next login was replaced with the mean of time spent on other activities within the same visit (see Figure 4). Although the exact amount of time spent on the last activity could not be measured, this provides a way of avoiding the inclusion of time passed without participation in learning activities.

Login frequency

How frequently learners participate in an online course has been considered to be an important factor predicting higher levels of performance. Piccoli, Ahmad, and Ives (2001) reported that learners’ login frequency into the LMS was highly correlated with course satisfaction in online learning. In a study measuring the correlation between frequency of participation and the grades achieved by college students, Davies and Graff (2005) argued that a significant association between frequency of participation in online activities and grades. Kang, Kim, and Park (2009) demonstrated that total login frequency in the LMS is directly connected with not only learning performance, but also attendance rate. Similarly, Hung and Zhang (2008) emphasized the significance of login frequency as a predictor of learner’s higher performance.

The instructor of the course analyzed in this study frequently uploaded learning material for learners to use in the class. It was therefore assumed that the more frequently learners logged into the LMS, the more newly updated and shared information they could obtain, which would lead to gaining a better understanding of the learning content as well as what needs to be prepared for the classes. The login frequency was calculated by adding up the number of individual student’s login time in the LMS.

The degree to which learners invest their time has been recognized as a factor correlative with learning performance; moreover, a great deal of research has reported a strong relationship between total studying time and performance (Beaudoin, 2002; Carroll, 1963; Hwang & Wang, 2004; Thurmond, Wambach, & Connors, 2002).

Studying time for the online course was calculated based on “login time,” since the actual learning in an online course mostly occurs while being logged in. To support the significance of the variable, the conception of learning time as suggested by Cotton and Savard (1981) was adopted (see Figure 3). In the study, learning time was comprised of three parts: Allocated Time (AT), Time-on-Task (TOT) and Academic learning time (ALT). This conception is illustrated as follows.

Regularity of login interval

Regularity of learning was presumed to represent learners’ consistent endeavors and awareness of their learning status throughout the course. Learners who want to achieve their learning goals while also engaging in outside work should exhibit perseverance with learning. It was assumed that learners with consistency in and awareness of their learning status study regularly. In fact, adult learners with multiple commitments to work, family, and study show the adoption of a regular routine to achieve their academic goals (Blaxter & Tight, 1994).

Regularity of login interval was calculated using standard deviation of the login interval. This basically indicates the “irregularity of the learning interval.” In the following figure (see Figure 5), the gap between A and B indicates the total course period, while $\Delta t1,2$ is the interval between the first and second login time, calculated by subtracting t1 from t2. In the same way, the nth interval can be obtained, presented as $\Delta tn-1, n$. Consequently, the mean of a learner’s login interval can be calculated, from which the variance is subsequently elicited, as indicated in Figure 6.

Figure 5. Concept of login interval

$$\text{Mean of learning interval: } \overline{\Delta t_i} = \frac{\sum_{i=1}^{n-1} \Delta t_i}{n}$$

$$\text{Standard deviation of learning interval: } S_i = \sqrt{\frac{\sum_{i=1}^{n-1} (t_i - \overline{\Delta t_i})^2}{n-1}}$$

Figure 6. Calculation of mean and standard deviation of login interval

Even when variation occurs in each learner's login duration and login frequency, the regularity of the login interval can be the same (see Figure 7). However, considering that total login time and login frequency were included as independent variables in the predictive model, learning regularity can indicate learners' efforts to keep themselves on right track throughout the course.

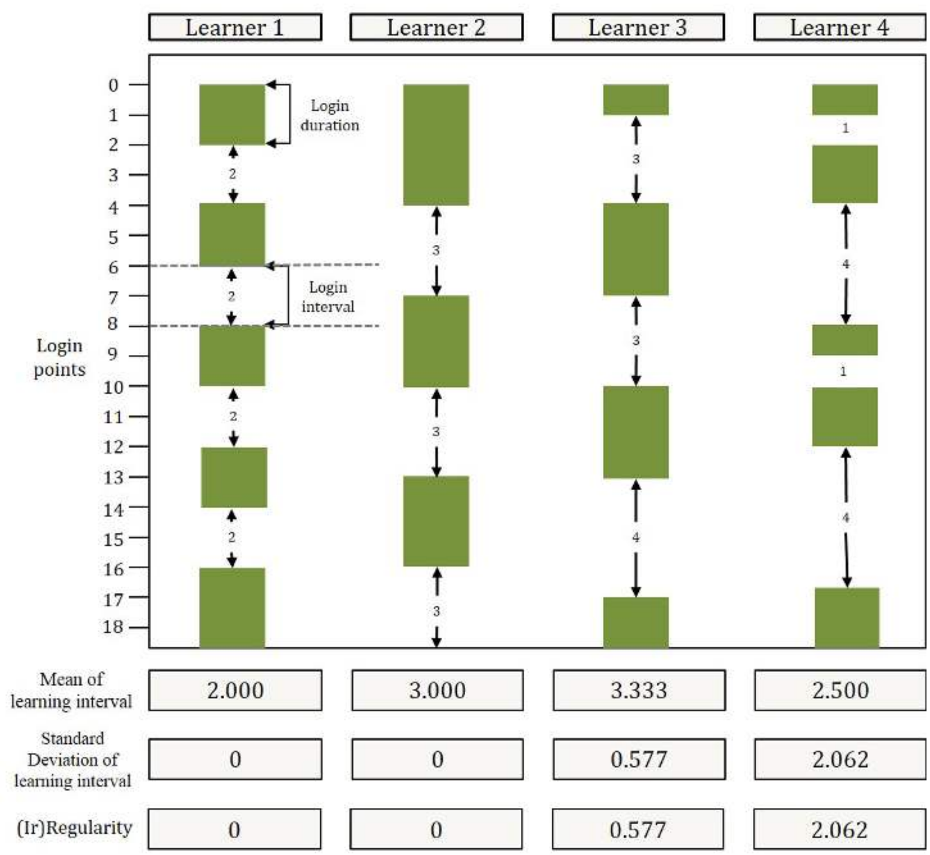

Figure 7. Example of calculating login regularity

Research questions

Whether or not e-learning is successful is primarily dependent upon how a learner who has autonomy in his/her own learning sustains consistent investment of time and effort. In particular, those adult learners who cannot fully engage only in their studies may become easily frustrated, as they suffer from perceived difficulties in managing time (Blaxter & Tight, 1994).

The purpose of this study was to propose proxy variables with regard to time management strategy by manipulating log data, as well as to examine whether the factors actually predict learning performance, as indicators of time management strategy. It is expected that such indicators will be conducive to providing precautionary feedbacks or interventions within an early stage based on the learner's status. In this study, the following research questions were addressed.

R1: How can candidates for proxy variables regarding adult learners' time management strategy be elicited from a log data set?

R2: Do the suggested variables (total login time, login frequency and regularity of login interval) predict adult learners' performance?

Methods

Participants and research context

The participants in this study were recruited from a commercial e-learning course entitled "Credit Derivative," administered by a Korean e-learning company. All of the 200 participants (53 male, 147 female) work full-time in the financial business field. The course aims to provide learners with knowledge about derivative products, such as its definition, relevant laws, strategy for safe investment, and interpretation of index numbers. Learners who complete the course are expected to be prepared for client consultation. All the participants voluntarily participated in the course, even though they were financially supported by their employers to do so. This course was operated 100% online for one month, and was comprised of 12 modules that provide one hour video lectures covering part of the textbook.

Along with the asynchronous video lectures, bulletin boards and relevant resources were provided in the LMS for learners to download learning materials and post questions. Learners were supposed to study the content in advance of each lecture and take a test at the end of the course. They were allowed to replay all videos for review.

Measures and variables

Suggested independent variables

Log data were collected from the LMS by an automatic collection module embedded within the system. The Total login time, Login frequency and (ir)regularity of login interval were extracted as independent variables.

Dependent variable

Learning performance, the dependent variable in this study, was defined as the score obtained on the final test, which consisted of 20 multiple choice items, each equally worth 5 points (See Table 1). The scores from each question were collected and added together in order to obtain the total score. The total score was graded on a scale of one hundred points, and ranged from 40 to 100. A unit of measurement of time was the hour, and Total login time and (ir)regularity of learning interval was calculated accordingly.

Table 1. Means and standard deviations of variables

Variables	Mean	Standard deviation
Total login time (hour)	38.18	14.46
Login frequency	46.31	12.56
(Ir)regularity of learning interval	2.92	2.05
Learning performance	77.92	15.09

Note. N = 200.

Results

Correlation analysis

Correlation analysis was conducted prior to multiple regression analysis to identify correlations among the independent and dependent variables (See Table 2). The results showed that (ir)regularity of the learning interval had a significant negative correlation with the final test score, defined as learning performance, and was also negatively correlated with Login frequency.

Table 2. Pearson's correlation of suggested variables and learning performance

	1	2	3	4
Total login time	1			
Login frequency	-.016	1		
(Ir)regularity of learning interval	-.064	$-.181^{*}$	1	
Learning performance	.035	$.141^{*}$	$-.597^{**}$	1

Note. $^{*}p < .05$. $^{**}p < .01$, (2-tailed).

Multiple linear regression analysis

Multiple regression analysis can be used to determine the significance of independent variables (Pedhazur, 1997). Since the primary focus of this study was to find a proxy variable which represents learners' time management strategy, multiple regression analysis was performed to determine which of the three candidates for proxy variables predict learning performance. The results are presented in Table 3.

The three suggested variables were found to account for 34.7% of the variance in learning performance ($F = 36.267$, $p < .01$). Of the three proxy variables, only (ir)regularity of learning interval was found to be a significant predictor of learning performance ($\beta = -.590$, $t = -10.115$, $p < .01$).

Table 3. Results of multiple linear regression analysis

Model	Unstandardized coefficients		Standardized coefficients			Collinearity statistics	
	B	Std. Error	Beta	*t*	*Sig.*	Tolerance	VIF
(constant)	76.672	4.511		19.680	.000		
Total login time	-.002	.060	-.002	-.034	.973	.995	1.005
Total login frequency	.041	.070	.034	.586	.559	.967	1.035
(Ir)regularity of login interval	-4.343	.429	-.590	-10.115	.000	.963	1.039
R^2 (adj. R^2) = .357 (.347), $F = 36.267$, $p = .000$, Durbin-Watson = 1.692							

Note. Dependent variable: Learning performance.

Discussion

This study primarily focused on providing a unique process to construct proxy variables based on previous studies and determining which candidate best predicts adult learners' performance. The results of the correlation analysis revealed that the (ir)regularity of login interval factor had a significant correlation with and was a predictor of learning performance. This was also supported by the results of multiple regression analysis, which also indicated (ir)regularity of login interval as a predictor of learning performance.

Although learning time and learning frequency have both been emphasized in previous studies as predictive factors positively affecting learner performance, it is hard to assume that either login time or login frequency of adult learners are directly translated into their ability to sustain effort and time investment throughout a course. Some research reported a limited relation between studying time and learning performance. For example, Ha and colleagues (2006) insisted that total studying time is not related to learning performance, while Lee (2007) highlighted the fact that learning performance can be increased only when the learners fully concentrate on what they do, regardless of the total amount of available time. Similarly, login frequency cannot fully explain whether the learners partook in meaningful learning. Although learners may access the LMS frequently, their actual studying time might be relatively short. It is also likely that they log into the LMS more intensively at a certain point rather than constantly participating in academic activities. Such tendencies have been reported to hinder well-planned learning, resulting from either procrastination or a lack of effective time use (Howell & Watson, 2007).

The regularity of the learning interval, unlike frequency, can provide critical evidence as to the fact that learners who log into the LMS more steadily from the beginning of a class to the end show better performance. This involves neither temporal access at a certain point nor merely one long time visit, but rather conscious learning with awareness over a relatively long term. Some studies have recognized regular participation as a vital key to success in learning (Britton & Tesser, 1991). Given that time management strategy has been considered to involve self-regulation, long-term planning and sustained efforts of the learners, the regularity of learning is expected to be a strong indicator of time management strategy.

Conclusion

This study was concerned with the fact that adult learners frequently fail in the completion of online courses due to poor time management strategy. Given the exponential growth of online learning in adult education, this issue should be given priority. Herein, a critical proxy variable that enables the prediction of at-risk adult learners was suggested, in terms of time management. From the perspective of adult learning, time management was investigated, as a key competency helping learners to achieve academic goals. The results indicated that the regularity of learning works as a powerful indicator of the learners' time management strategy, as it represents consistent effort and awareness to sustain perseverance with the pursuit of learning in a manner that could not be fully explained by the other two variables examined. It was discovered that adult learners accomplish successful completion of an online course when they maintain consistent awareness throughout the course. We expect this finding will contribute to the area of online adult learning.

An innovative approach to constructing proxy variables was also provided herein. As opposed to previous studies which largely relied on an inductive approach to the analysis of data, we attempted to build a solid foundation that enables more reliable data processing. The data processing method employed in this research can be applied to similar contexts where learners mostly engage in lecture-based courses, such as in the Massive Open Online Course or Open Course Ware emerging as a new trend in higher and adult education (Holford, Jarvis, Milana, Waller, & Webb, 2014). The process of constructing proxy variables showed the possibility of application in further research to investigate more sophisticated proxy variables representing other conceptual factors.

Until now, a large amount of research in the field of learning analytics and educational data mining has been conducted in a data-driven way, and frequently, with scarce theoretical background (Ferguson, 2012). Recently, however, learning analytics research is placing increased emphasis on learning and teaching theories as well, in contrast to its strong roots as a data-driven approach (Zaïane, 2001). The social and pedagogical usage of learning analytics is currently being actively discussed (e.g., Baker & Corbett, 2014) as researchers search to define it as a separate field by which to improve learning opportunities away from the business area (Ferguson, 2012; Jo, Kim, & Yoon, 2014; Long & Siemens, 2011). We expect that the balanced consideration of theory and data will lead to advancement in data-oriented research.

This study had several limitations. First, the specific time use of the participants could not be tracked due to technical limitations. For example, it could not be determined whether the learners were playing or pausing the lectures. With the log data, which better mapped actual time use on more specific behaviours, a more accurate analysis to capture real studying time could be made possible. Despite the fact that the total login time was used as an indicator of extensive studying time, the learners may have been greatly distracted by irrelevant information, a factor which would result in lower learning performance compared to that indicated by the recorded time. If the learner's specific time use in LMS can be tracked, thus allowing extraction of the actual studying time from the log data at every moment, it would be possible to investigate the relationship between studying time and learning performance more clearly.

Furthermore, this study relied entirely on empirical verification in order to elicit the proxy variable. Although empirical verification is meaningful in certain contexts, the problem of concurrent validity can be posed when applied to other contexts. For substantiating concurrent validity, the use of an existing questionnaire measuring time management strategies can be considered for comparison.

Our ultimate goal is to develop an integrated LMS that provides precautionary intervention based on the diagnosis of learners made from the use of proxy variables. Future research should address the design and development of such interventions. For example, an LMS equipped with a monitoring function which employs proxy variables can be developed so that learners can be provided with opportunities to monitor their status of learning with a formative assessment view, which would enable reflection on their level of accomplishment. The development of such a learning management interface can be extended not only to providing more detailed interventions, but also toward supporting the continuous self-development of learners.

Acknowledgements

This work was supported by a grant from the National Research Foundation of Korea, funded by the Korean Government (NRF-2013S1A5A2A03044140).

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