

# Analyzing the Log Patterns of Adult Learners in LMS Using Learning Analytics

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## ABSTRACT

In this paper, we describe a process of constructing proxy variables that represent adult learners' time management strategies in an online course. Based upon previous research, three values were selected from a data set. According to the result of empirical validation, an (ir)regularity of the learning interval was proven to be correlative with and predict learning performance. As indicated in previous research, regularity of learning is a strong indicator to explain learners' consistent endeavors. This study demonstrates the possibility of using learning analytics to address a learner's specific competence on the basis of a theoretical background. Implications for the learning analytics field seeking a pedagogical theory-driven approach are discussed.

## Categories and Subject Descriptors

K.3.1 [Computer and Education]: Computer Uses in Education -Distance Education

## General Terms

Measurement, Human Factors.

## Keywords

Learning Analytics, Big-data mining, Log data, Time Management Strategy, Adult Education.

## 1. INTRODUCTION

There are high demands within e-learning for adult learners. Over the past years, there have been an increase in online course enrollment among adult learners in order to obtain knowledge or develop professional skills [6, 17, 38]. However, difficulties have also been posed by adult learners in taking online courses due to their lack of time management skills [22].

Time management strategies are increasingly required in the

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context of adult learning because they are usually involved in both their study and job at the same time; therefore, a successful completion of an online course depends on the efficient use of a given amount of time. To a considerable degree, it is reported that failure in an online course for adult learners results from poor time management [11, 19].

By analyzing adult learners' online activity based on educational data mining, instructors can detect the status of their learning processes in an earlier stage. Given that most activities of learners enrolled in online courses occur in a Learning Management System (LMS), utilizing the log data within the LMS could provide crucial insight into the learning analytics field. If we can distinguish the learning patterns in the early stage of an online course, it will be conducive to encouraging or guiding learners by providing them with an appropriate instructional intervention [4].

Log data, which is saved as an unstructured data set, contains users' log information within online systems, and 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 from surveys, which rely highly on learners' recall and subjective interpretations; thus, we do not have to consider the possibility of distortion or low reliability [1, 12]. However, log data alone cannot be transferred to the learning processes without a sophisticated interpretation in regards to theoretical aspects. Our contribution is to suggest an effective way to convert users' log data into predictive indicators of learning performance based on theoretical background.

The focuses of this study are twofold. First, we elicit "candidates for proxy variables" from the log data set that represent learners' time management strategies as conceptual constructs which have long been considered to be a vital factor to their performances[2, 26, 31, 34, 42]. Second, we determine whether the elicited proxy variables predict learner performance in terms of verifying the empirical validity. If so, the proxy variables can be used to detect the status of learners' time management and predict performance in other data sets from similar contexts.

## 2. PROXY VARIABLES TO REPRESENT TIME MANAGEMENT STRATEGY IN LMS

Converting a gigantic data set into proxy variables involves the following steps (see Fig. 1). First, the targeted conceptual construct should be discussed based on previous research. Theories addressed in previous research should dictate the manipulation of data; further, necessary values, such as learning

time range, clicking point, login and logout time calculated from data set, are selected in order to be used as the construct variables. Then, proxy variables are elicited through the process. In essence, by considering the theoretical aspect, we can determine what should be included from the manipulated values.

The proxy variable, which is not identical to the targeted conceptual construct but is optimally processed, can be applied to other data sets. In this study, three variables are chosen on the basis of previous studies.

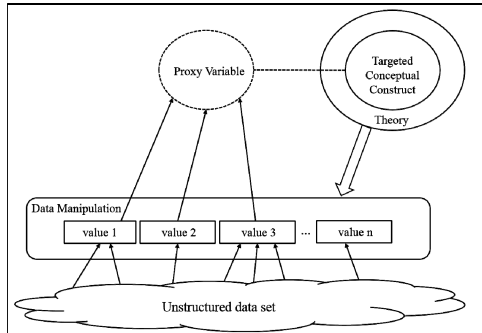


Figure 1. A conceptual framework for the construction of a proxy variable

### 2.1 Time management strategy

A large body of research argued that time management strategy is deeply associated with the ability to prioritize tasks [18, 26]. In the study to determine whether time management strategy attenuate adult learners' strain, Kaufman-Scarborough and Lindquist [18] perceived prioritizing tasks as an essential factor, which leads an individual to a value judgment. Jex and Elacqua [21] reported that the prioritization of tasks is one of key factors that comprises time management competence of those who well organize their work. Meanwhile, within the perspective that regards it as a sub-element of self-regulated learning, researchers have emphasized the efficient use of time [15, 31, 32, 42]. The concept of the efficient use of time has incorporated a series of sub-factors, such as sufficient amount of time investment on tasks and active participation [9, 29, 39]. On the other hand, a long-range planning has been considered to be a crucial factor for explaining time management strategy [2, 11]. By sustaining an appropriate amount of time and 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. In essence, time management strategy in learning can be defined as an effective use of time by prioritizing the given tasks while sustaining the consistent endeavors.

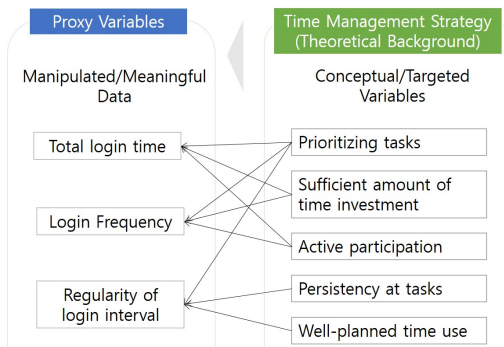


Fig. 2. Selection of three variables.

Fig. 2 presents the relationship between each potential proxy variable and sub-element of the time management strategy as a targeted conceptual construct. As learners are required to invest their time on their study in order to obtain an expected score for completing the course while still having to work, the amount of the total login time and the login frequency is regarded, to some extent, as prioritization of the course over their work. The assumption is in accordance with previous studies, which regard time management as a technique for having sufficient time to accomplish the required tasks [33, 39]. Likewise, the relationship between regularity of login interval and prioritizing tasks can be posited if we consider that learners who value the course are likely to access the LMS regularly in order to obtain updated information as well as not to get left behind.

### 2.2 Total login time

The degree to which learners invest their time has been recognized as a powerful factor correlative with performance; moreover, much research has reported a strong relationship existent between the total studying time and performance [37].

In this study, “total studying time” is represented by the term “total login time,” to measure the actual learning time. To support the significance of the variable, Cotton and Savard’s conception of learning time was adopted [7] (see Fig. 3). In the study, learning time can be categorized into three parts: Allocated Time (AT), Time-on-Task (TOT) and Academic learning time (ALT); this conception is illustrated as follows.

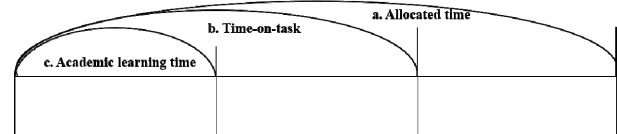


Figure 3. Three types of studying time

In this study, the author argued that the three different types of time mentioned above are significantly correlated with learning performance. Of course, it is hard to regard login time as genuine academic learning time because merely logging into LMS does not necessarily denote meaningful learning in itself. However, we can easily assume that recorded login time belongs with the allocated time or time-on-task when considering that the greatest proportion of learning-related activities occur within LMS, such as observing lectures, gathering information, interacting with peers or submitting assignments.

Therefore, we decided to use the login time to construct the proxy variable as an indicator standing for the allocated time, which is an extended concept in which two other types of time are inherent.

### 2.3 Login frequency

How frequently learners participate in an online course has been regarded as an important factor that predicts higher levels of performance. Piccoli, Ahmad, and Ives [30] reported that learners’ login frequency into LMS is highly correlated with course satisfaction in online learning. Davies and Graff [8] argued that participation frequency within online activities is significantly associated with their grades. Kang, Kim, and Park [20] demonstrated that total login frequency into LMS is directly connected with not only learning performance, but also attendance rate.

In this study, we assume that the more frequently learners log into LMS, the more newly updated and shared information they shall obtain, which is a factor that leads to their better understanding of the learning content as well as what they must prepare for classes. The login frequency was calculated by adding up the number of individual student's login time into LMS.

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## 2.4 (Ir)regularity of learning interval

Regularity of learning is defined as the extent to which learners regularly engage in learning, and has been recognized as one of the time management strategies [10]. Many researchers have found that the regularity of learning positively predicts learning performance [28, 35].

In this study, data is calculated into a standard deviation of the login interval. Thus, it basically indicates the "irregularity of learning interval." To be specific, in the following (see Fig. 4), the gap between A and B indicates the total course period, and  $\Delta t_{1,2}$  is an interval between the first and second login time calculated by subtracting  $t_1$  from  $t_2$ . In the same way, we can obtain nth, the interval which is presented as  $\Delta t_{n-1, n}$ . Consequently, the mean of the learner's login interval can be calculated, and the standard deviation is subsequently elicited from the mean, as indicated in Fig. 5.

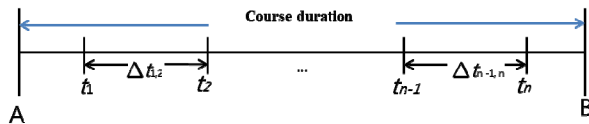


Figure 4. Concept of learning interval

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

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

Figure 5. Calculation of mean and standard deviation of learning interval

## 3. RESEARCH QUESTIONS

The specific research questions are as follows.

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

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

## 4. ANALYSIS AND RESULTS

### 4.1 Participants and research context

The participants in this study consisted of 200 adult learners enrolled in a commercial e-learning course entitled "Credit Derivative" administered by a Korean e-learning company. All participants were engaged in the financial business field as their

full-time job. This course is operated 100% online over a month. At the end of the course, all participants were required to take a test.

## 4.2 Measures and Variables

### 4.2.1 Suggested independent variables

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

### 4.2.2 Dependent variable

Learning performance, a dependent variable in this study, is defined as a score of the final test, which consisted of 20 multiple choice items. 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.

Table 2. Means, standard deviations of variables (n=200)

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

## 4.3 Multiple Linear Regression Analysis

A multiple regression analysis was conducted in order to determine whether the three suggested values, which serve as proxy indicators of time management strategy, predict learning performance. The results are presented in Table 3.

It is shown that the suggested three variables account for 20.8% of the variance in learning performance ( $F=36.267$ ,  $p < .01$ ).

Of these three proxy variables, only (ir)regularity of learning interval was found to predict learning performance ( $\beta=-4.343$ ,  $t=-10.115$ ,  $p < .01$ ).

Table 4. Results of multiple linear regression analysis

Model	Unstandardized		Standardized	t	Sig.
	B	Std. Error	Beta		
(constant)	88.772	4.511		19.680	.000
Total studying time	-.002	.060	-.002	-.034	.973
Total login frequency	.041	.070	.034	.586	.559
(Ir)regularity of learning interval	-4.343	.429	-.590	-10.115	.000
$R^2$ (adj. $R^2$ ) = .597 (.347), $F=36.267$ , $p = .000$					

a. Dependent Variable: Final grade

## 5. DISCUSSION

The result reveals that only the (ir)regularity of learning interval factor is proven to predict learning performance.

Indeed, some of the research reported a limited relation between studying time and learning performance. Ha and colleagues [14], insisted that total studying time is not related to learning performance, and Lee [23] highlighted the fact that learning performance can be increased only when learners are fully concentrated on what they do, regardless of the total amount of available time. Similarly, login frequency cannot fully explain learners' meaningful learning. Although learners access LMS frequently, learners' actual studying time might be relatively short. It is also likely that they intensively log into LMS at a certain point rather than constantly participating in academic activities. Such a tendency has been reported to hinder well-planned learning, resulting in either procrastination or a lack of effective time use [16].

The regularity of the learning interval, meanwhile, can provide critical evidence as to the fact that learners who more steadily log into LMS from the beginning of a study to the end show better performance. This involves neither a temporal access at a certain point nor merely a one long time visit, but rather a well-intended and conscious learning over a relatively long term. As a matter of fact, several articles recognize regular participation as a vital key to success in learning [3, 25, 26, 41]. Given that the time management strategy has been considered to involve the learner's self-regulation, long-term planning and sustaining efforts, the regularity of learning is expected to be a strong indicator of time management strategy.

## 6. CONCLUSION

This study has made a contribution to learning analytics, within the context of an adult learner's time management strategy which has been considered to be an essential factor for successful learning in andragogy [5].

This study shows a process of converting complex log patterns into elaborated "proxy variables" based on both a ripe theoretical foundation and well-intended manipulation. It demonstrates a possibility of further research regarding the formation of more sophisticated proxy variables that represent certain conceptual constructs drawn from an enormous database. Until now, much research in the learning analytics field has been conducted in a data-driven way and frequently with scarce theoretical background [13]. Recently, however, the learning analytics field has constantly maintained its emphasis on the learning and teaching areas as well in contrast to its strong root as a data-driven approach [40]. The social and pedagogical usage of learning analytics is being actively discussed now, as researchers search to define it as a separate field by which to improve learning opportunities away from business area [13, 24]. Along this line, an abundant theoretical foundation is required for the extensive application of research findings into the real world context.

This study has limitations as well. We could not track the specific time use of the learners. With log data which better mapped a variety of time use on different menus and web pages, a more accurate analysis to catch real studying time could have been made possible. If we can track the learner's specific time use in LMS and thus extract actual studying time from log data at every moment, it would be possible to more clearly

investigate the relationship between genuine studying time and learning performance.

## 7. REFERENCES

- [1] Baker, R. S. J. 2010. *Data Mining For Education*. In *International Encyclopedia of Education* (3rd edition), B. McGaw, Peterson, P., Baker Ed. Oxford, UK.
- [2] Barling, J., Kelloway, E. K. and Cheung, D. 1996, "Time management and achievement striving interact to predict car sale performance", *Journal of Applied Psychology*, 81, 821-6.
- [3] Britton, B. K. and Tesser, A. 1991. Effects of time-management practices on college grades. *Journal of Educational Psychology*, 83(3), 405-410.
- [4] Brown, M. 2011. Learning Analytics: The Coming Third Wave. EDUCAUSE Learning Initiative Brief, Retrieved from <http://www.educause.edu/Resources/LearningAnalyticsTheComingThir/227287>.
- [5] Clardy, A. 2005. *Andragogy: Adult learning and education at its best?* EBSCOhost online submission. (ERIC Document Reproduction Service No. ED492132)
- [6] Cohen, E. B. and Nycz, M. 2006. Learning objects and e-learning: An informing science perspective. *Interdisciplinary Journal of Knowledge and Learning Objects*, 2, 23-34. Available at <http://ijklo.org/Volume2/v2p023034Cohen32.pdf>.
- [7] Cotton, K. and Savard, G. W. 1981. Time factors in learning. Research on school effectiveness project: Topic summary report. Retrieved from <http://search.proquest.com.access.ewha.ac.kr/docview/63544228?accountid=10785>.
- [8] Davies, J. and Graff, M. 2005. Performance in e-learning: Online participation and student grades. *British Journal of Educational Technology*, 36(4), 657-663.
- [9] Davis, M.A. 2000. "Time and the nursing home assistant: relations among time management, perceived control over time, and work-related outcomes", *paper presented at the Academy of Management*, Toronto.
- [10] Eastmond, D. V. 1993. Adult learning of distance students through computer conferencing. Unpublished doctoral dissertation. New York: Syracuse University.
- [11] Eastmond, D. V. 1998. Adult learners and Internet-based distance education, *New Directions for Adult and Continuing Education* 78, 33-41.
- [12] Elias, T. 2011. Learning analytics: Definitions, processes and potential. Creative Commons.
- [13] Ferguson, R. 2012. The state of learning analytics in 2012: a review and future challenges. Technical Report No. KMI-12-01, Knowledge Media Institute, The Open University <http://kmi.open.ac.uk/publications/techreport/kmi-12-01>
- [14] Ha, C. S., Kim, J. H., Choi, H. C., and Yoo, H. S. 2006. The relationships among self-control, class engagement, learning time after school, and academic achievement in Korean adolescents. *Studies on Korean Youth*, 17(1), 181-200.

- [15] Hofer, K. H., Yu, S. L., and Pintrich, P. R. 1998. Teaching college students to be self-regulated learners. In Schunk, D. H. & Zimmerman, B. J. (Ed.), *Self-Regulated Learning from Teaching to Self-Reflective Practice*. NY: Guilford Press.
- [16] Howell, A. J., and Watson, D. C. 2007. Procrastination: Association with achievement goal orientation and learning strategies. *Personality and Individual Differences*, 43, 167-178.
- [17] Hrastinski, S. 2008. Asynchronous & synchronous e-learning. *Educause Quarterly*, 31(4), 51-55.
- [18] Jex, J. M., & Elacqua, T. C. (1999). Time management as a moderator of relations between stressors and employee strain. *Work and Stress*, 13, 182-191.
- [19] Joo, Y., Jang, M., and Lee, H. 2007. An In-depth analysis of dropout factors based on Cyber University Student's Dropout Experiences, *The Journal of Educational Information and Media*, 13(3), 209-234.
- [20] Kang, M., Kim, J., and Park, I. 2009. The examination of the variables related to the students' e-learning participation that have an effect on learning achievement in e-learning environment of cyber university. *Journal of Korean Society for Internet Information*, 10(5), 135-143.
- [21] Kaufman-Scarborough, C., & Lindquist, J. D. 1999. Time Management and Polychronicity: Comparisons, Contrasts, and Insights for the Workplace, *Journal of Managerial Psychology* 14 (3-4), 288-312.
- [22] Kwon, S. 2009. The Analysis of differences of learners' participation, procrastination, learning time and achievement by adult learners' adherence of learning time schedule in e-Learning environments, *Journal of Learner-Centered Curriculum and Instruction*, 9(3), 61-86.
- [23] Lee, Y.S. 2007. Redesigning time-lined structure diagram analysis and active learning time diagram analysis for the consulting and self-analysis of teaching. *The Journal of Yeolin education*, 15(2), 21-49.
- [24] Long, P. and Siemens, G. 2011. 'Penetrating the fog: analytics in learning and education', *EDUCAUSE Review*, 46(5), 31-40.
- [25] Loomis, K. D. 2000. Learning styles and asynchronous learning: Comparing the LASSI model to class performance. *Journal of Asynchronous Learning Networks*, 4(1). 23-31.
- [26] Macan, T.H., Shahani, C., Dipboye, R.L. and Philips, A.P. 1990. "College students time management: correlations with academic performance and stress". *Journal of Educational Psychology*, 82, 760-768.
- [27] Merriam, S. B. (2001). Andragogy and self-directed learning: Pillars of adult learning theory. In S. B. Merriam (Ed.), *The new update on adult learning theory* (pp. 3-14). San Francisco, CA: Jossey-Bass.
- [28] Moore, R. 2003. Attendance and performance: How important is it for students to attend class?. *Journal of College Science Teaching*, 32(6), 367-371.
- [29] Orpen, C. 1994, "The effect of time-management training on employee attitudes and behaviour: a field experiment", *The Journal of Psychology*, 128, 393-396.
- [30] Piccoli, G., Ahmad, R., & Ives, B. 2001. Web-based virtual learning environments: a research framework and a preliminary assessment of effectiveness in basic IT skill training. *MIS Quarterly*, 25(4), 401-426.
- [31] Pintrich, P. R. and DeGroot, E. V. 1990. Motivational and self-regulated learning components of classroom academic performance. *Journal of educational psychology*, 82, 33-40.
- [32] Pintrich, P. R., Smith, D. A. F., Garcia, T., and McKeachie, W. 1993. Reliability and predictive validity of the Motivated Strategies for Learning Questionnaire (MSLQ). *Educational and Psychological Measurement*, 53, 801-813.
- [33] Slaven, G. and Totterdell, P. 1993, "Time management training: does it transfer to the workplace?". *Journal of Managerial Psychology*, 8, 20-28.
- [34] Song, L., Singleton, E. S., Hill, J. R., and Koh, M. H. 2004. Improving online learning: Student perceptions of useful and challenging characteristics. *Internet and Higher Education*, 7, 59-70.
- [35] Stanca, L. 2006. The effects of attendance on academic performance: panel data evidence for introductory microeconomics, forthcoming, *Journal of Economic Education*. 37(3), 251-266.
- [36] Tak, S.Y., Park, Y.S., and Kim, U.C. 2006. With specific focus on parent-child relationship, self-efficacy, 24achievement motivation and hours of study: Factors influencing academic achievement of university students. *Child Education*, 16(1), 143-154.
- [37] Thurmond, V. A., Wambach, K., and Connors, H. R. 2002. Evaluation of student satisfaction: determining the impact of a web-based environment by controlling for student characteristics. *The American Journal of Distance Education*, 16(3), 169-189.
- [38] Wang, M., Vogel, D., and Ran, W. 2011. Creating a Performance-Oriented E-Learning Environment: A Design Science Approach. *Information & Management*, 48(7), 260-269.
- [39] Woolfolk, A.E. and Woolfolk, R.L. 1986, "Time management: an experimental investigation", *Journal of School Psychology*, 24, 267-75.
- [40] Zaiane, O.R. 2001. 'Web usage mining for a better web-based learning environment', *paper presented at The 4th IASTED International Conference on Advanced Technology for Education (CATE'01)*, 27-28 June, Banff, Canada.
- [41] Zariski, A. and Styles, I. 2000. Enhancing student strategies for online learning. In A. Herrmann and M. M. Kulski (Eds.), *Flexible futures in tertiary teaching. Proceedings of the 9th Annual Teaching Learning Forum 2000*. <http://lsn.curtin.edu.au/tlf/tlf2000/zariski.html>
- [42] Zimmerman, B. J. 2002. Becoming a self-regulated learner: An overview. *Theory Into Practice*, 41(2), 64-72.