A Course Level Analysis of Academic Performance on Adult Learners

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Thanks, in part, to the rapid development and widespread adoption of the Internet and other online technologies, academic institutions are increasingly using analytics to enhance learning and teaching. Through the use of data mining techniques, this study examines some of the determinants at a course level that affect the academic performance of adult learners (which we will refer to as students in this paper) in the Singapore University of Social Sciences (SUSS). Formerly known as SIM University, SUSS is an institution that caters mainly to the learning needs of working adults although it offers a number of full-time undergraduate degree programmes to fresh school leavers. The data analysis found that students taking introductory blended courses performed better than those who took face-to-face courses of the same level. Furthermore, students of similar age taking level-2 courses outperformed students taking similar courses where the age difference was more significant. The findings indicate that no single optimal course design will lead to improved academic performance across all courses. Instead, educators should be ready to consider the nature, level, discipline and coursework component of each course to cater to the various students' needs.

Keywords: blended learning, course design, data mining, academic performance

Introduction

The Singapore University of Social Sciences (SUSS) is a university dedicated to providing lifelong education to equip learners to serve society. It offers part and full-time degree programmes and courses to both working adults and fresh school leavers. To cater to the distinctive needs of these two segments, SUSS offers face-to-face and, increasingly, blended courses that combine the unique features and benefits of face-to-face and online delivery and seeking, in the process, to increase its students' learning and academic performance and, ultimately, its retention rates.

To date, the literature on determinants associated with academic performance are mainly at the students' level and there appears to be a dearth of research on the determinants that impact the students' academic performance at a course level. This study aims to bridge this gap by focusing on the determinants that affect students' performance at a course level. Using data mining techniques such as decision trees, this research examines how certain course characteristics such as course delivery mode (blended or face-to-face), course discipline, nature of the course (qualitative, quantitative or mixed), assessment method (written examination or project) and course level (1 to 4), can be combined with socio-demographic data to identify groups of students whose academic performance, represented by their average final score, is superior to that of other groups. The remaining sections discuss the literature relevant to the scope of this study, the methods used and the data analysis that was carried out to derive the findings that are then explained and discussed in the context of SUSS.

Recommendations for the design of courses based on the research findings and suggestions for future research are presented in the concluding section.

Literature Review

Blended Learning

Garrison and Vaughan (2008) define blended learning as "the thoughtful fusion of face-to-face and online learning experiences" where "face-to-face oral communication and online written communication are optimally integrated such that the strengths of each are blended into a unique learning experience congruent with the context and intended educational purpose."

In terms of delivery modes, courses can be categorised along a continuum delimited, at one pole, by traditional, face-to-face courses and, at the opposite end, by fully online courses, with web-facilitated and blended courses falling somewhere in between (Rovai & Jordan, 2004).

Although such an exercise remains somewhat subjective, there have been attempts to determine the characteristics that distinguish each delivery mode category. For instance, Allen and Seaman (2015) suggest a classification based on the proportion of the content of a course that is delivered online. According to them, a traditional course is a face-to-face course if none of its content is delivered online (0%). On the other hand, it is a web-facilitated course if it is a face-to-face course that has anywhere from 1% to 29% of its content delivered online. It becomes a blended course when it blends face-to-face and online delivery and has between 30 and 79% of its content delivered online and finally, it is an online course if most of its content is made available online (80% and above) and if it does not feature any face-to-face teaching at all.

More recently, a number of other authors have subdivided blended learning into blended synchronous and blended asynchronous learning (Bower et al., 2014; Wang, Choon & Hu, 2017). A blended synchronous learning environment is one in which the same lesson is delivered simultaneously to both classroom and online students while in a blended asynchronous environment, a face-to-face session is carried out in the physical classroom and another is delivered online via technologies such as a learning management system (Wang, Choon & Hu, 2017). Up until 2010, most SUSS courses were delivered exclusively through six classroom-based, three-hour, face-to face sessions that combined one-way, lecture-style instructions and instructor-led tutorials. Following Allen and Seaman's delivery classification, these were essentially traditional courses.

In 2010, however, SUSS started a transition towards its own blended teaching and learning model so as to better meet the learning needs of its students and enhance their learning experience. The initial six classroom-based, three-hour face-to-face sessions of most courses have been converted into 6 asynchronous online chunked lectures (series of short, pre-recorded lectures) that students view at their own time and pace. These six fully-online sessions are complemented by 3 face-to-face, classroom-based seminars featuring frequent instructor-students and student-student interactions. According to Allen and Seaman's classification, the university moved away from traditional, face-to-face courses and is now offering what are essentially blended asynchronous courses.

At the same time, depending on whether the nature of subject required more face-to-face interactions (strategy and business negotiations, for instance), certain courses still offer six face-to-face sessions instead of 3, while keeping the same other delivery features of the blended courses. In the context of this research, these courses are known as face-to-face courses.

Academic Performance and Its Determinants

Any undertaking aimed at predicting academic performance must begin by determining the means to assess it. The measure of academic performance is based on the achievement of learning outcomes.

The learning outcomes of many courses, including those offered as part of degree programmes offered by SUSS, are developed according to Bloom's taxonomy of the cognitive domain, one of the three domains of learning (the other two being the affective and the psychomotor domains). Bloom's taxonomy divides the cognitive domain into six learning hierarchical categories that rank cognitive processes from the simplest to the more complex intellectual skill development: knowledge, comprehension, application, analysis, synthesis and evaluation (Bloom, et al. 1956).

Along with standardised admission tests such as the SAT (previously known as the Scholastic Achievement Test or the Scholastic Aptitude Test) and the American College Testing (ACT), the grade-point average (GPA) is the most common quantitative measure of cognitive skills and abilities acquisition that educational researchers have used as a proxy for a student's academic performance (Richardson et al., 2012; Plant, 2005; Chemers, 2001). The GPA is the weighted mean of the final mark that a student obtained from each course in the basket of courses that s/he completed towards the completion of a formal academic qualification (Richardson et al.,2012). Despite its popularity, the GPA is not without its flaws as a measure of academic performance: grade inflation affects its validity in longitudinal studies and its reliability is particularly low for studies comparing GPA differences across institutions (Didier, et al. 2006).

A number of correlational analyses have used the GPA at different stages of a student's study progression, either as a dependent or as an independent variable. For instance, in studies examining the factors that may influence the students' academic performance at the university, researchers have used the high-school or pre-university GPA among the independent variables that may affect the students' undergraduate academic performance, expressed in terms of their university final or cumulative GPA, the dependent variable (McKenzie, 2001).

Vulperhorst et al. (2018) concluded that students' high school grade point average (GPA) is a good predictor of academic performance in higher education.

Evidence to the critical importance that policy-makers, employers, educators and students lend to academic success, the body of research seeking to examine the factors that influence a student's undergraduate academic performance is both large and varied.

In the literature, the effect of socio-demographic factors on performance is somewhat inconclusive. Age, for instance, seems to matter as some studies found that older students do academically better than their younger counterparts (Clifton et al., 2008; Etcheverry, Clifton, & Roberts, 2001). Other studies, however, did not reach the same conclusion as they could not establish the same relationship (Farsides & Woodfield, 2007; Ting & Robinson, 1998). In a more recent study, El Massah & Fadly (2017) examined the academic performance of female finance students and found age to have an insignificant effect on performance. On the other hand, a number of studies did find that women and students from higher socio-economic background in the US and Europe tend to achieve higher GPA than other students (Dennis, Phinney, & Chuateco, 2005; LaForge & Cantrell, 2003; Smith & Naylor, 2001).

Similar to the case of age, the effect of gender on academic performance is also inconclusive. Hyde and Kling (2001) concluded that female students often performed better than male students in all measures of success in higher education. Sheard (2009) also shared similar findings that female students outperformed their male counterparts for each measured academic assessment criterion. In an earlier study by McCrum (1994), he suggested that males performed academically better than females as there were more males who obtained firstclass honours degrees than females at Oxford University and Cambridge University. In a more recent study, Danilowicz-Gösele et al. (2017) found that gender was not a significant factor in determining students' academic performance.

Prior academic performance and aptitude tests results have also caught the attention of researchers seeking to identify what may help predict academic success. In that respect, a number of studies identified some of the traditional measures of cognitive capacity (SAT and ACT) and high school results as reliable predictors of university academic performance (Ellias, 2007; Plant, 2005; Robbins, 2004), although some found that of the two, high school GPA appears to be a stronger predictor than standardised tests such as SAT and ACT (Richardson, 2012).

The influence of the delivery mode on academic performance has been at the centre of "No Significant Difference" in the academic performance debate between educators who promote online and blended (sometimes called "hybrid") learning and those who largely dismiss them as less-than-effective teaching and learning models.

According to Russell (2001), the findings of a very significant body of research and meta-analyses generally concur that there is indeed no significant difference in students' learning outcomes based on delivery mode. The conclusions of more recent meta-analyses and studies are not as definite. Means et al. (2010), the authors of a US Department of Education report, conducted a meta-analysis of 45 prior studies done between 1996 and 2008 on the topic of delivery modes and learning outcomes. Comparing blended and fully online courses, they concluded that 7 studies found no significant difference between these delivery modes, 2 found statistically significant advantages for purely online instruction, and one found an advantage for blended instruction. However, study findings comparing blended and face-to-face delivery modes were clearer: on average, students who took blended courses perform significantly better than did those taking traditional, face-to-face courses (Al-Qahtani & Higgins, 2013; Lack, 2013; Melton, Graft & Chopal-Foss, 2009).

Method

In this study, the final grade distributions of 837 courses were obtained for 2015. Student information such as gender, age, race (Chinese, Malay, Indian and others), school of enrolment, prior academic institution and prior academic performance, as well as O-Level (Secondary 4) English and O-Level Mathematics performance were aggregated to the course level (e.g. proportion of male students and average age of students in a course). Course level information such as the school offering the course, the semester the course was offered, course discipline, course level, mode of final assessment, weighting of the final assessment in the final grade, qualitative flag, quantitative flag and course delivery mode, together with the student information, were included as inputs in this study. Details of the variables are provided in Table 1. These inputs are evaluated with respect to the performance of the students. The descriptive statistics of the courses are summarised in Table 2.

A total of 541 undergraduate courses in SUSS (or 64.6% out of the 837 courses in 2015) were included in the analysis. These courses had at least 50% of complete student information. An average grade point based on the final grade distribution of the students was computed for each course, using the same algorithm as that for the computation of honours classification. This average grade point was further grouped into 2 categories: courses with an average grade point corresponding to the second class honours classification and above (termed as "Better" for ease of reference) and courses with a lower average grade point (termed as "Average"). This variable "Class" comprises the variable of interest, or target (variable) in the analysis. Of the 541 courses included in the study, 217 courses were classified as "Better" and the remaining 324 courses "Average".

Table 1: Variables used to evaluate the performance of students at a course level

Variable Names	Description
Class	Average performance of students in the course
School	School offering the course
Discipline	Discipline to which the course belongs
Level	Course level
ExamMode	Mode of final assessment
Weighting	Weighting of the final assessment to the final grade
Qualitative	Whether the course is qualitative in nature
Quantitative	Whether the course is quantitative in nature
CourseMode	Delivery mode of the course
Female	% of students in the course who belong to the gender
Male	
Race 1 to 4	% of students in the course who belong to the race
School 1 (mainly social services)	% of students in the course who enroll in the school
School 2 (mainly social sciences)	
School 3 (mainly business)	
School 4 (mainly science and technology)	
Prior institution 1 to 6	% of students in the course who previously study at the institution
Age Mean	Average age of the student
Age Standard Deviation	Standard deviation of the students' age
'O' Level Math Mean	Average prior Math performance
'O' Level Math Standard Deviation	Standard Deviation of the students' prior Math performance
'O' Level English Mean	Average prior English performance
'O' Level English Standard Deviation	Standard Deviation of the students' prior English performance
Prior Academic Mean	Average prior academic performance
Prior Academic Standard Deviation	Standard Deviation of the students' prior academic performance

Collection and analysis of data associated with learning comprise the core of learning analytics (Brown, 2011). The last decade has witnessed an increase in the adoption of learning analytics in educational institutions. This is not surprising as learning analytics offers a promising approach to better discern students' learning behaviours to improve their retention and success through appropriate intervention (Tseng and Walsh, 2016). In this learning analytics study, data mining was used to analyse the data to gain a better understanding of the learning environment and its outcomes.

Table 2: Descriptive statistics of the course variables

Variable Name	Possible Values	Count	Percentage
Class	Average	324	59.9%
	Better	217	40.1%
Course School	Sch1 (mainly social services)	77	14.2%
	Sch2 (mainly social sciences)	86	15.9%
	Sch3 (mainly business)	141	26.1%
	Sch4 (mainly science and technology)	237	43.8%
Discipline	29 unique disciplines		
Level	1 (introductory)	113	20.9%
	2	214	39.6%
	3	199	36.8%
	4 (advanced)	15	2.7%
ExamMode	Project/Take-home examination	81	15.0%
	In-Class written examination	460	85.0%
Weightage	High (>50%)	240	44.4%
	Low (<=50%)	301	55.6%
Qualitative	0	93	17.2%
	1	448	82.8%
Quantitative	0	421	77.8%
	1	120	22.2%
CourseMode	Blended	295	54.5%
	F2F	246	45.5%

Data for all the 541 courses were used to build the model. Decision trees (C5.0, CHAID, C&RT and QUEST) were used to evaluate course performance and its determinants in blended and face-to-face courses. CHAID emerged as the best model to explain the students' course performance with an accuracy rate of 67.1%. N-fold cross-validation was used to compute the model's estimated error rates with as little bias as possible (Braga-Neto& Dougherty, 2004).

In n-fold cross-validation, the dataset is randomly split into n mutually exclusive subsets (also known as folds). The model is then built with n-1 folds based on the decision tree parameters and an accuracy rate is calculated by testing the model using the remaining fold (Rodriguez et al., 2010). The model accuracy rate is then aggregated across n folds to give the overall accuracy rate for the validated model. In this study, we have chosen n to be 5.

An illustration of n-fold cross-validation is shown in Figure 1, where the folds in continuous line are the ones to build the model and fold in dotted line to validate the model.

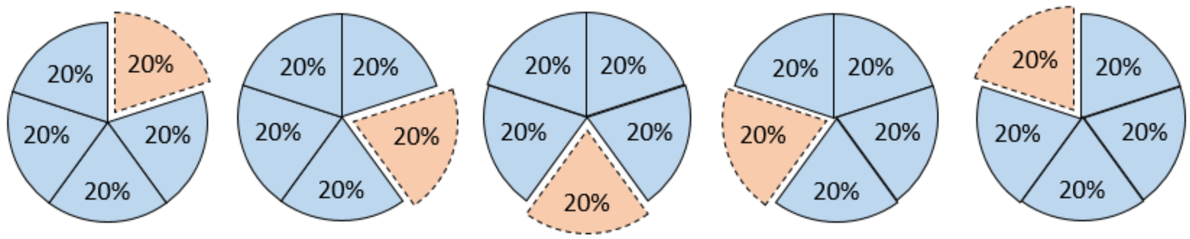

Figure 1: Graphical presentation of the 5-fold cross-validation procedure

Results and Discussion

As mentioned earlier, the CHAID decision tree is selected as the final model with an overall accuracy rate of 67.1% (see left side panel in Figure 2). The n-fold cross-validation overall accuracy rate is 67.5% (see right side panel in Figure 2). Figure 2 shows a summary of the results.

CLASS	Average	Better
Average	227	97
Better	81	136

Overall Accuracy =	67.10%
Accuracy for Average =	70.06%
Accuracy for Better =	62.67%

CLASS	Average	Better
Average	236	88
Better	88	129

Overall Accuracy =	67.47%
Accuracy for Average =	72.84%
Accuracy for Better =	59.45%

Figure 2 In-sample and holdout - Accuracy rates of the model

A better understanding of the course performance and its determinants in blended and face-to-face courses can be seen from the decision tree in Annex A. This study focused on the determinants that affect adult students' performance at a course level. Three main findings can be discussed.
For level-1 (introductory) courses, students performed better in blended courses than they did in face-to-face courses (see Nodes 4 and 5). When viewed from a learning outcome perspective, such a conclusion is not surprising.

As explained in the literature review, the learning outcomes of the courses offered by SUSS follow Bloom's taxonomy. The learning outcomes of level-1 SUSS courses focus on knowledge recall as well as on the basic comprehension of the more fundamental concepts and theories underlying a particular subject or discipline.
The learning outcomes of levels 2, 3 and 4 SUSS courses, on the other hand, target increasingly more sophisticated intellectual skills as they seek to develop the students' ability to understand, apply, analyse and evaluate the material that they study. Melton, Graf, and Chopak-Foss (2009) explain that students in blended learning courses are more responsible for learning content on their own time than in classical, face-to-face, classroom-based teaching and learning situations. As such, to achieve the more basic learning outcomes of level-1 courses where knowledge acquisition and comprehension are the aims, students need to invest their own time to simply read and absorb the morefundamental theories and concepts contained in the course material.
Because these two tasks cannot be effectively delegated to a teacher, students taking level-1 course would normally require fewer interactions with their instructor and lesser discussions with their peers than they would need for level 2, 3 and 4 courses where the learning is deeper and the material covered, more advanced and more complex.

Early each semester, students taking level-1 blended courses at SUSS are reminded that the only 3 face-to-face sessions will be dedicated to class discussions and small-group activities that are tapping on the knowledge thatthey are expected to have acquired prior to coming to class. This study findings seem to confirm that these students heed this advice as they do better than students taking level-1 courses using a traditional delivery approach.

It is conceivable that students taking level-1, traditional face-to-face courses with 6 face-to-face sessions do not perform as well because they tend to be over-reliant on their instructor's guidance instead of putting in their own time and effort to absorb the knowledge contained in the course material.

As to the age-academic performance relationship, the decision tree does show that the more homogeneous the age of the students taking level-2 courses, the better their academic performance was (see Nodes 6 and 7).
The link between age differences, course level and academic performance is somewhat harder, but not impossibleto explain when also considering the students' profile and their study progression.

It is often during the very first semester of their programme of study that students take level-1 courses at SUSS.As working adults enrolled in part-time studies, they have little time to mingle with their peers so unless they believe that they cannot cope alone with the demands of their courses, they prefer learning on their own. Level-1 courses are ideal for this opportunity. As discussed earlier, their learning material is relatively easier to absorb and their

learning outcomes less ambitious than higher level courses so students are able to and given their other work, family and other commitments, they prefer studying alone.
SUSS offers learning opportunities for working adults who are 21 years old and above. While the average age of SUSS students is 27, one can find, in any course, students who are anywhere between 21 and 55 or even older.

Empirical evidence suggests that students tend to mingle and collaborate with those who are more of less of the same age, possibly because they might more easily relate to one another on a personal basis.

In situations where the age difference between the students is low, students can more easily pair up with others of a similar age, help one another study and learn better. For those reasons, students perform better in these courses.

Finally, students tend to perform better for more advanced qualitative exam-based courses offered by Schools 1,

3 and 4 (See Nodes 20 and 21). This finding came as a surprise as the bulk of the courses are from School 4 which offers mainly Science and Technology courses. One possible explanation could be that the courses are mainly management related such as aviation change management and project management and these students are able to apply what they have learnt from their jobs to their studies.

Conclusion

This study aims to gain a better understanding of the determinants associated with the performance of adult learners at a course level. A notable finding is that blended courses might improve learning and performance only for specific courses that are at a level 1 (introductory) level.

For more advanced level courses, face-to-face delivery might be more suitable. Also, based on the findings, universities can consider grouping students who are more homogenous in age for lower level courses to help them get into peer and group learning. (Further analyses on
age differentials by course, course level and school for the various relevant nodes were conducted and no significant age differential was found.) Finally, blended courses seem to be more appropriate for courses that are qualitative in nature.

Further studies can be expanded to use larger datasets to include more courses and students to enhance the generalisability of the findings. Future research can also consider the role of faculty and course assessments in comparing the students' learning experience and academic performance.

It is hoped that this study has provided insights into the effects of the course and student attributes on the academic performance of students, and the determinants of such effects at a course level.

References

Allen, I. E., & Seaman, J. (2015). Grade level - Tracking online education in the United States. Retrieved from http:// www.onlinelearningsurvey.com/highered.html

Al-Qahtani, A. A., & Higgins, S. E. (2013). Effects of traditional, blended and e-learning on students' achievement in higher education. Journal of Computer Assisted Learning, 29, 220-234. https://doi.org/10.1111/j.1365-2729.2012.00490.x

Bloom, B.S. (Ed.). Engelhart, M.D., Furst, E.J., Hill, W.H., Krathwohl, D.R. (1956). Taxonomy of Educational Objectives, Handbook I: The Cognitive Domain. New York: David McKay Co Inc.

Bower, M.; Dalgarno, B.; Kennedy, G.; Lee, M. G. W., & Kenney, J. (2014). Blended Synchronous Learning - A Handbook for Educators. Sydney: Office for Learning & Teaching.

Brown, M. (2011). Learning analytics: The coming third wave. EDUCAUSE Learning Initiative Brief, 1(4).

Braga-Neto, U. M., & Dougherty, E. R. (2004). Is cross-validation valid for small-sample microarray classification? Bioinformatics, 20(3), 374-380.

Chemers, M. M., Hu, L.-T., & Garcia, B. F. (2001). Academic self-efficacy and first year college student performance and adjustment. Journal of Educational Psychology, 93(1), 55-64. https://doi.org/10.1037/0022-0663.93.1.55

Clifton, R. A., Perry, R. P., Roberts, L. W., & Peter, T. (2008). Gender, psychosocial dispositions and the academic achievement of college students. Research in Higher Education, 49, 684-703. https://doi.org/10.1007/s11162-008-9104-9

Conard, M. A. (2006). Aptitude is not enough: How personality and behavior predict academic performance.Journal of Research in Personality, 40, 339-346. https://doi.org/10.1016/j.jrp.2004.10.003

Danilowicz-Gösele, K., Lerche, K., Meya, J., & Schwager, R. (2017). Determinants of students' success at university. Education economics, 25(5), 513-532. https://doi.org/10.1080/09645292.2017.1305329

Dennis, J. M., Phinney, J. S., & Chuateco, L. I. (2005). The role of motivation, parental support, and peer support in the academic success of ethnic minority first-generation college students. Journal of College Student Development, 46, 223-236. https://doi.org/10.1353/csd.2005.0023

Didier, T., Kreiter C. D., Buri, R., Solow, C. (2006). Investigating the utility of a GPA institutional adjustment index. Advances in Health Sciences Education, 11(2), 145-153. https://doi.org/10.1007/s10459-005-0390-0

El Massah, S. S., & Fadly, D. (2017). Predictors of academic performance for finance students: Women at higher education in the UAE. International Journal of Educational Management, 31(7), 854-84.

Elias, S. M., & MacDonald, S. (2007). Using past performance, proxy efficacy, and academic self-efficacy to predict college performance. Journal of Applied Social Psychology, 37(11), 2518-2531. https://doi.org/10.1111/j.1559-1816.2007.00268.x

Etcheverry, E., Clifton, R. A., & Roberts, L. W. (2001). Social capital and educational attainment: A study of undergraduates in a faculty of education. Alberta Journal of Educational Research, 47, 24-39.

Farsides, T., Woodfield, R. (2007) Individual and gender differences in good and first-class undergraduate degree performance. British Journal of Psychology, 98(3). pp. 467-483 https://doi.org/10.1348/000712606X150246

Garrison, R., & Vaughan, N. D. (2008). Blended learning in higher education: Framework, principles, and guidelines (1st ed.). San Francisco, CA: Jossey Bass.

Hyde, J. S., & Kling, K. C. (2001). Women, motivation, and achievement. Psychology of Women Quarterly, 25(4), 364-378. https://doi.org/10.1111/1471-6402.00035

Lack, K. A. (21 March 2013). Current Status of Research on Online Learning in Postsecondary Education. Retrieved from http://sr.ithaka.org/sites/default/files/reports/ithaka-sr-online-learning- postsecondaryeducation-may2012.pdf

LaForge, M. C., & Cantrell, S. (2003). Explanatory style and academic performance among college students beginning a major course of study. Psychological Reports, 92, 861-865. https://doi.org/10.2466/pr0.2003.92.3.861

McCrum, N. G. (1994). The academic gender deficit at Oxford and Cambridge. Oxford Review of Education, 20(1), 3-26. https://doi.org/10.1080/0305498940200101

McKenzie, K., & Schweitzer, R. (2001). Who Succeeds at University? Factors predicting academic performance in first year Australian university students. Higher Education Research & Development, 20(1), 21-33. https://doi.org/10.1080/07924360120043621

Means et al. (2010) Evaluation of Evidence-Based Practices in Online Learning: A Meta-Analysis and Review of Online Learning Studies, (Washington D.C., U.S. Department of Education, 2010), www2.ed.gov/rschstat/eval/tech/evidence-based-practices/finalreport.pdf.

Melton, B., Graf, H., & Chopak-Foss, J. (2009). Achievement and satisfaction in blended learning versus traditional general health course designs. International Journal for the Scholar- ship of Teaching and Learning, 3(1), 1-13 https://doi.org/10.20429/ijsotl.2009.030126

Plant, E. A., K. Anders Ericsson, Hill, L., & Asberg, K. (2005). Why study time does not predict grade point average across college students: Implications of deliberate practice for academic performance. Contemporary Educational Psychology, 30, 96-116. https://doi.org/10.1016/j.cedpsych.2004.06.001

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. Psychological Bulletin, 138(2), 353-387. https://doi.org/10.1037/a0026838

Robbins, S. B., Lauver, K., Davis, H. L. a. D., & Langley, R. (2004). Do psychosocial and study skill factors predict college outcomes? A meta-analysis. Psychological Bulletin, 130(2), 261-288. https://doi.org/10.1037/0033-2909.130.2.261

Rodriguez, J. D., Perez, A., & Lozano, J. A. (2010). Sensitivity analysis of k-fold cross validation in prediction error estimation. IEEE Transactions On Pattern Analysis And Machine Intelligence, 32(3), 569-575. https://doi.org/10.1109/TPAMI.2009.187

Rovai, A. P., & Jordan, H. M. (2004). Blended learning and sense of community: A comparative analysis with traditional and fully online graduate courses. International Review of Research in Open & Distance Learning, 5(2), 1-12. https://doi.org/10.19173/irrodl.v5i2.192

Russell, T. L. (2001). The No Significant Difference Phenomenon: A Comparative Research Annotated Bibliography on Technology for Distance Education (5th ed.). Raleigh, NC: North Carolina State University.

Sheard, M. (2009). Hardiness commitment, gender, and age differentiate university academic performance. British Journal of Educational Psychology, 79(1), 189-204. https://doi.org/10.1348/000709908X304406

Smith, J., & Naylor, R. (2001). Determinants of degree performance in UK universities: A statistical analysis of the 1993 student cohort. Oxford Bulletin of Economics and Statistics, 63, 29-60. https://doi.org/10.1111/1468-0084.00208

Ting, S. R., & Robinson, T. L. (1998). First-year academic success: A prediction model combining cognitive and psychosocial variables for European and African Americans. Journal of College Student Development, 39, 599-610.

Tseng, H., & Walsh, Eamonn Joseph Jr. (2016). Blended versus traditional course delivery: Comparing students' motivation, learning outcomes, and preferences. Quarterly Review of Distance Education, 17(1), 43-52,56.

Vulperhorst, J., Lutz, C., de Kleijn, R., & van Tartwijk, J. (2018). Disentangling the predictive validity of high school grades for academic success in university. Assessment & Evaluation in Higher Education, 43(3), 399-414. https://doi.org/10.1080/02602938.2017.1353586

Wang, Q.; Quek, C. L.& Hu, X. (2017). Designing and improving a blended synchronous learning environment: An educational design research. International Review of Research in Open and Distributed Learning, 18(3), 99-118. https://doi.org/10.19173/irrodl.v18i3.3034

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