A Learning Analytics Approach to the Evaluation of an Online Learning Package in a Hong Kong University

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Abstract: In recent years, research using learning analytics to predict learning outcomes has begun to increase. This emerging field of research advocates the use of readily-available data to inform teaching and learning. The current case study adopts a learning analytics approach to evaluate the online learning package of an academic English course in a university in Hong Kong. This study aims to (1) explore the completion pattern of use of the online learning package by students in a generic undergraduate academic skills course; and (2) predict student outcomes based on their online behaviour patterns. Over three academic years, the study examined usage logs for 7000+ students that were available on the university's learning management system. Student assessment component scores, online activity completion rates, and online behavioural patterns were identified and examined using descriptive analysis, bivariate correlation analysis, and multiple regression analysis. The findings reveal insights into different online learning behavioural patterns that would benefit blended course designers. For instance, some students started using the online learning package early in the semester but fulfilled only the minimum required online work, whereas others greatly exceeded the basic requirement and continued doing activities in the online package even after the semester had finished. The relationship between learning activities in the online package and assessment component grades was found to be weak but meaningful. A regression model was developed drawing on the completion rates to predict overall student scores, and this model successfully identified several specific factors, such as total number of attempts and performance in individual online learning activities, as predictors of the final course grade.

Keywords: learning analytics, blended learning; online learning package, English for academic purposes, Hong Kong, course design

1. Introduction

When Hong Kong's university curriculum changed in 2012 from a three-year structure (British system) to a four-year one (American system), the university in question seized the opportunity to introduce a substantial blended learning component to its new English subjects via a Learning Management System (LMS). The introduction of the LMS was primarily driven by two considerations. First, the new English courses were offered in the form of one 3-hour session per week (instead of one 2-hour session and one 1-hour session), a change that gave students considerable time to study and complete their work before their next class. Second, since blended learning approaches around the globe have proven successful, the university's course designers built on studies that identified the benefits of blended learning for students in a higher education context over the last decade (e.g. Fischer, 2007; Huon, et al., 2007), in order to include a blended learning component in their new English for Academic Purposes (EAP) courses.

When the first four-year curriculum cohort was in their final year of study, it was felt that a more comprehensive curriculum review was warranted. Despite receiving excellent feedback from stakeholders such as students, teachers, and external reviewers through the institution's quality assurance mechanism, students' online behaviour and the nature of their engagement with online learning components remains under-explored. Therefore, the current study set out to examine students' behaviour with regard to the online learning package more closely, in order to inform future blended learning designs for the EAP context. For more details of the full curriculum review, see Chen (2018) and Chen, Foung and Armatas (2018).

This study adopts a data-driven approach to understand the behaviours of students completing blended learning activities and to explore the impact of blended learning tasks to course assessment. This study is highly relevant and important to the field of Computer-Assisted Language Learning and EAP because (1) understanding the behaviors of students facilitates more effective development of blended learning activities; and (2) establishing the relationship between blended tasks and course performance can help evaluate the effectiveness of blended task in an evidence-based manner.

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The next section presents a literature review on the establishment of learning analytics as a research interest in Computer-Assisted Language Learning (CALL) and how it facilitates CALL design. This is followed by a methodology section that introduces the course, participants, CALL activities, and data analysis procedures adopted in the current learning analytics study. The findings are then presented and discussed, including the general pattern of completion, the 'cut-off' effect, the acquisition of writing skills, and a predictive model for overall grades. The article concludes with a number of suggestions for blended learning teachers and researchers.

2. Literature Review

The use of learning analytics in the field of Computer-Assisted Language Learning (CALL) can contribute to developing an understanding of students and their behaviours in completing blended learning tasks. Various previous studies drawing on learning analytics have successfully explained how students' self-regulating behaviours affect their performances and engagement in blended learning activities (e.g. Fischer, 2007; Zacharis, 2015; Zheng, et al., 2016). Students who can self-regulate and attain goals engage best in a blended environment (Arispe and Blake, 2012). In addition to this principle, several other aspects have proven to be important areas in blended learning research, including student behaviours in an online environment, effective learning design, and the association between blended tasks and their outcomes.

In recent decades, research has attempted to understand the online behaviours of students in various blended learning contexts. Unsurprisingly, students tend to be rather pragmatic when approaching blended learning; that is, they acquire knowledge to obtain good marks, instead of aiming to broaden their knowledge (Huon, et al., 2007). Some CALL learners could even be described as adopting a 'principle of minimal effort' approach (Fischer, 2007, p.419). This aligns with the findings of previous empirical studies (e.g. Li, 2014) that students complete necessary online learning tasks without doing more than the minimum required for learning. Despite this, blended learning designs are still being promoted, since diversity in a carefully-planned course delivery approach can create better learning experiences (Kahn, et al., 2017). For example, the diversity and interaction between delivery modes in blended learning is likely to improve students' satisfaction with the course (Naveh, Tubin and Pliskin, 2010; Zacharis, 2010). Teacher presence seems to be particularly effective in enhancing the effectiveness of online material delivery (Hegeman, 2015). In Hegeman's study, teacher presence refers to the adoption of teacher-prepared notes, instead of consulting external websites for help or clarification. This is echoed in a recent review by Nortvig, Petersen, and Balle (2018) that states that educator presence is a dominating factor influencing e-learning and learning outcomes. Another key influencing factor is the deliberate connections designed into the learning activities of the online and offline parts of a course. Online and offline activities should be integrated so that learning can expand from the classroom to out-of-class learning, and vice versa.

Blended learning research has also focused on identifying effective blended learning designs and understanding learner preferences, and these aspects provide further insights into blended learning in a language-learning context. Generally speaking, students are becoming more comfortable with online learning via a Learning Management System, and feel that such online learning can help improve their course performance (Uziak, et al., 2018). According to Arispe and Blake (2012, p.459), students with poor spoken language proficiency tend to prefer traditional blended learning materials (i.e. one-way delivery/without the presence of an instructor) which allow them to learn at their own pace without being 'overwhelmed' by an instructor. They believe that students with poor spoken language proficiency can enjoy their learning in the online component of a blended learning course, as there is no instructor asking them to respond to questions spontaneously. Li (2014) also suggests that when given the opportunity to choose how they want to fulfil their blended learning requirement, some students prefer to do web exercises, while others prefer to interact with peers via online group discussions. Zhu, Au, and Yates (2016) believe that text-heavy online tasks (such as keeping an online journal or responding to a discussion thread) can help activate certain self-regulated learning behaviours, such as planning and reflection, and thus these exercises play a significant role in blended learning. Heift (2003) examined the impact of different types of web task on student learning. She believes that some exercises allow for more freedom (e.g. drag-and-drop and gap-filling activities), while others provide a lower degree of freedom (e.g. multiple-choice questions). Here, freedom refers to the fact that students do more than simply click the correct answer (as in MC questions), but move the mouse to answer a question online (as in drag-and-drop exercises). Activities that allow for more freedom were found to have a more significant impact on students' learning. These studies suggest that the types of activity that are made available (e.g. discussion, multiple-choice questions, drag-and-drop, or gap-filling) can affect students' learning. Hershkovitz and Nachmias (2011) believe that further research is needed in this domain to extend our understanding of students' online behaviours in blended teaching and learning contexts.

In addition to students' online behaviours, predicting students' learning outcomes appears to be important within the blended learning research paradigm, with learning outcome used as a common way to define the effectiveness of e-learning (Noesgaard and Ørngreen, 2015). Sceptics have argued that the relationship between delivery mode and student outcomes is generally rather weak (Dziuban and Moskal, 2011; Moskal, Dziuban and Hartman, 2013); however, other academics have continued to explore such relationships by including different factors in their predictive models. Several studies have concluded that participatory variables, such as course login frequency, reading course announcements, and accessing course materials, are significant predictors of final course grades (Chen, 2013; Chen and Jang, 2010; Damianov, et al., 2009; Dawson, McWilliam and Tan, 2008; Tempelaar, Rienties, and Giesbers, 2015; Zacharis, 2015; Zhu, Au and Yates, 2016). Macfadyen and Dawson (2010) identified some influential participatory variables, such as total number of discussion messages posted, total number of mail messages sent, and total number of assessments completed. Some studies have also evaluated the predictive power of other factors; for example, one study found that students' motivation predicts their performance (Zhu, Au and Yates, 2016), while another study concluded that other demographic factors, such as university entrance exam marks, can be good predictors of students' performance and final scores in a blended learning course (López-Pérez, Pérez-López and Rodríguez-Ariza, 2011).

Other than these e-learning-based studies, it is important to take note of some learning analytics studies using advanced data mining techniques, such as Asif, Merceron, Ali, and Haider (2017) and Foung (2019). They also attempted to explore ways to predict students' performance and have not yet included blended learning variables. The data mining methods such as classification trees and logistics regression analysis can be applied to blended learning studies to predict students' performance and this was echoed by Rodrigues, Zárate, and Isotani (2018).

However, little research has been conducted to explore how blended learning components can predict final course grades. Only a few studies have confirmed that online activities performance can predict students' final results (e.g. Macfadyen and Dawson, 2010; Tempelaar, Rienties and Giesbers, 2014). Hence, there is room for further investigation in this respect.

Despite past efforts to understand students' online behaviours and the role of blended learning in the development of academic writing skills, there is still room for a learning analytics approach to assess these and to explore the predictors of learning outcomes in blended academic skills courses. To be precise, this study aims to answer the following questions:

1. How many online activities did students complete?
2. How much time did students spend on online activities?
3. Is the 'pragmatic' approach to online activities applicable to the current context? If so, how?
4. Can students' behavioural patterns in blended learning components predict their academic outcomes?

3. Methodology

The following sections describe how the research was conducted with the readily-available data on the LMS and detail how the course and its online activities were designed.

3.1 Participants

This study adopted a convenience sampling approach and retrieved the learning data of students taking a university English course, English for University Studies (EUS) from the university LMS between 2012/13 and 2014/15. In other words, entries were retrieved as long as they were available and no probabilistic computation was involved in acquiring the data. The learning data of 7,156 students were eventually retrieved for analysis, most of which comprised the access log data available on the LMS, such as which learning activities students had selected, when students had commenced working on the learning activities, and what scores they had received for each activity.

3.2 Ethical Clearance

The Ethical Review for Teaching/Research involving human subjects of this project was approved by the Departmental Research Committee and recorded on the university Human Subjects Ethics Application Review System (Reference Number: HSEARS20160812002).

3.3 Course and Assessments

EUS is a foundation EAP course taken by two groups of students at different English proficiency levels. Most students attain a Level 4 in English in the Hong Kong secondary school exit examination (equivalent to an IELTS [International English Language Testing System] score of 6.30–6.51) while the remaining students attain Level 3 in the same exam (equivalent to an IELTS score of 5.48–5.56). Students who attain a Level 3 must first take a proficiency-based English course, followed by EUS, the foundation EAP course. Meanwhile, Level 4 students take EUS as their first English course in university. In the data set selected for the current study, 33.6% of students took this course as their second English course (Level 3), while 66.4% took this as their first English course (Level 4).

The aim of EUS is to develop students' English language proficiency for university study. There are two very similar versions of the course, catering respectively to students who primarily use APA/Harvard referencing styles and to those who mainly use IEEE/Vancouver referencing styles in their university studies. All students must complete the same assessments and fulfil the same assessment requirements. In 2012/13, each semester lasted for 14 weeks, but this was reduced to 13 weeks in 2012/13; thus, there were also only 13 weeks in each semester in 2013/14 and 2014/15.

In order to pass the course, students taking EUS must complete three assessments and independent online learning task (IndiWork) requirements. The first assessment comprises an in-class writing assignment focusing on a problem-solution essay, while the second one comprises a take-home expository essay. Finally, the third assessment comprises an in-class pair work presentation. These three assessments contribute to the final course grade. In addition, students must fulfil an 80% attendance requirement and an e-learning requirement, which is the focus of this study, called IndiWork. The minimum score for IndiWork in 2012/2013 was 60%, and that for 2013/14 and 2014/15 was 50%. Failure to meet any of these requirements will lead to an overall grade reduction, but completing more than the minimum will not lead to an improvement in the overall grade.

3.4 IndiWork

The aim and design of IndiWork is to provide students with extended and out-of-class learning opportunities related to the subject's learning outcomes. Hence, the content of IndiWork is directly relevant to the course content, that is, academic writing and academic speaking. All activities were developed by course designers with experience in teaching generic academic skills and were reviewed by the subject leader of the course. Each IndiWork activity comprises an individual web exercise with several questions posted on the university LMS; most activities adopt a gap fill, mix and match, and/or multiple-choice format. Some activities may ask students to watch a tailor-made video posted on YouTube before completing the exercise and some provide textual pre-task input for students. As an example, a list of blended learning activities in 2014/15 is presented in Appendix One. Students were offered a total of 15 learning activities in 2012/13 and 18 activities in 2013/14 and 2015/16. Although there were minor changes to the activities across cohorts in the years studied, the activities remain comparable in terms of content and level of difficulty. Most IndiWork activities are relevant to the EAP course, such as 'paragraph cohesion' and 'paraphrasing and summarising', while the remaining activities relate to general proficiency, such as vocabulary building. Depending on the course schedule, some IndiWork tasks are made available at the beginning of the term and expire in the middle of the term. For example, academic style is taught as the first unit of the course, so IndiWork activities on academic style start at the beginning of the term and expire in the middle of the term. Due to the teaching schedule, most other tasks are made available later in the term and expire at the end of the term. The course designers hope that this approach will motivate students to complete a class-related exercise soon after/before they have learned the corresponding skill in class.

Among the IndiWork activities that are available, students can choose which they want to complete to fulfil the minimum requirement. All activities are automatically and immediately marked by the system, and students know their total score for the activity and which items they have completed correctly. The total score of each individual IndiWork activity will count towards the overall IndiWork score. Students have unlimited attempts to do any activity, but only the score of the final attempt counts towards the IndiWork total score.

3.5 Data collection and procedures

Assessment results and IndiWork records are stored on the LMS; a list of variables is presented in Table 1. All teachers make use of this system to enter four component grades for each assessment for each student, and the system derives a final grade based on the component grades that are entered. The overall grade used for this study is calculated based on the overall assessment grades of the three assessments. The component grades for the written assessments are Content, Organization, Language, and Referencing, whereas those for spoken assessments are Content, Delivery, Language, and Pronunciation and Fluency. The University common assessment scheme specifies that students be assigned one of nine possible ordinal scores: 4.5, 4.0, 3.5, 3.0, 2.5, 2.0, 1.5, 1.0, 0, with 4.5 denoting 'Outstanding', 3.0 'Good', C 'Satisfactory', 1.0 'Barely Adequate', and 0 'Inadequate'.

Students' IndiWork records are available on the LMS for students to see. The IndiWork total score is the most important indicator, ranging from 0 to 1 (i.e. 0% to 100%), due to its direct implications for the overall grade (for details, see section 3.3 on Course and Assessments), and has been converted to a decimal number. To facilitate the analysis in this study, students were divided into seven groups according to their IndiWork scores: Group 1 for students from 0–0.25 completion; Group 2 (0.25–0.4999%); Group 3 (0.5–0.5999); Group 4 (0.6–0.6999); Group 5 (0.7–0.7999); Group 6 (0.8–0.8999); and Group 7 (0.9–1). On top of the total scores, the date and time of completing the IndiWork tasks were recorded by the system. The day that a student started an IndiWork task and the day on which a student finished his/her latest IndiWork task were also computed. In addition, for analysis purposes, the number of days between the first and last days was computed. In terms of the score for each IndiWork activity, the score for students' latest attempt in each activity and the number of total attempts were retrieved. Since each IndiWork activity corresponded to one or more assessment components (i.e. each IndiWork activity was designed to help students with at least one of the assessment components), the sum of all relevant IndiWork scores for a particular component was computed for analysis.

Table 1: List of Variables Retrieved from the Learning Management System (LMS)

Groups of Variables	Range
Level of English Public Exam	3–4
Overall Course Grade	0–4.5
IndiWork Total Score	0–1.0
Individual Component Scores of IndiWork	0–1.0

3.6 Data Analysis

After the data were retrieved, some entries were removed to maintain a valid data set. The records of students who, for various reasons, could not complete the course were removed. Next, a round of exploratory and descriptive analysis was conducted, including bivariate correlation analysis and descriptive statistics for various variables. After the exploratory stage, rounds of data testing and screening were carried out. Normality tests were performed with all relevant variables by visually inspecting the histogram. After the data cleaning procedures, several inferential statistical analyses, including bivariate correlation analysis and multiple regression, were conducted using IBM SPSS 23.

Because some parts of the dataset were not directly comparable, descriptive analysis was conducted for each individual student cohort. To allow generalizability, scores in activities were grouped under common categories, such as 'Unit 2 Activity on General Referencing'. Because the mean scores of each activity were used, such categories may represent the mean scores of two activities in 2012/13 or three activities in 2013/14. This use of mean scores made comparison across cohorts possible.

To conduct the multiple regression analysis, several assumptions needed to be met; thus, a number of steps were taken to ensure the validity of the analysis. First, the tolerance of included variables was checked to see if it was greater than 0.1. No variables presented violated this threshold. Unusual points were also detected and removed. The unusual points were standardized residual (> |3|) and Cook's distance (> 1) (Cook and Weisberg, 1982). Ultimately, 35 entries were deleted due to unusual standardized residuals. Next, the normality of the residuals was verified by visually inspecting the histograms and residuals in both models and confirming whether both were normally distributed. Finally, the analysis was run for a second time and the findings are presented and discussed in the next section.

4. Results and Discussion

The following sections examine how students completed the online activities designed for them, how these tasks facilitate acquisition of academic writing skills, and whether students' academic outcomes can be predicted with the variables related to blended learning components.

4.1 An Overview of IndiWork Completion

i. Completion Rate

Generally speaking, a high proportion of students completed the IndiWork activities. Tables 2a and 2b show the completion rates of IndiWork in different cohorts. The mean completion rate was 74.32% (2012/13; required minimum = 60%) and 62.06% (2013/14 and 2014/15; required minimum = 50%); in total, 94.7% of students completed the requirement (≥ 60%) in 2012/13 and 95.2% (≥ 50%) in 2013/14 and 2014/15. Among those students who met the requirements, a significant number (32.4% in 12/13; 26.2% in 13/14 and 14/15) did 10% more than the minimum required (Tables 2a and 2b).

Table 2a: IndiWork Total Score 2012/13 (*n* = 2,241; minimum required: 60%)

	Percent	Cumulative Percent
0 – 24.99%	.2	.2
25% – 49.99%	1.1	1.2
50% – 59.99%	2.6	3.9
60% – 69.99%	35.9	39.8
70% – 79.99%	27.8	67.6
80% – 89.99%	20.3	87.9
90% – 100%	12.1	100.0
Total	100.0	

Mean = 74.32%

Table 2b: IndiWork Total Scores 2013/14 & 2014/15 (*n* = 4,915; minimum required: 50%)

	Percent	Cumulative Percent
0 – 24.99%	.5	.5
25% – 49.99%	3.7	4.2
50% – 59.99%	52.1	56.3
60% – 69.99%	17.6	73.9
70% – 79.99%	12.6	86.5
80% – 89.99%	9.1	95.6
90% – 100%	4.4	100.0
Total	100.0	

Mean = 62.06%

The high completion rate across all three cohorts of students (2012/13 to 2014/15) shows that students were mindful of the course's e-learning completion requirement. Although meeting the minimum requirement does not lead to a higher course grade, failure to complete IndiWork results in a reduction of the course grade. This seems to provide a sufficiently strong incentive for students to engage with e-learning. A more in-depth analysis of completion rates and their effect will be discussed in section 4.1.3 on 'Cut-off Effect' following the presentation of some other e-learning parameters below.

ii. Time Spent on IndiWork

While a last-minute rush would make the IndiWork less relevant to student learning, the analysis showed that, in fact, most students did not complete their IndiWork within the last few weeks of the semester, but spread it over an average timespan of eight weeks. On average, students took approximately eight weeks to complete IndiWork between the first and last days of the semester (8.96 weeks for 2012/13; 7.31 weeks for 2013–2015; Table 3). With the EUS course lasting for 13 weeks in 2013/14 and 2014/15, the seven-week time interval recorded in these years seems sensible, in that students spent half the semester engaged in e-learning tasks. In 2012/13, students began earlier (in the first 1.5 weeks) and worked for approximately nine (i.e. 8.96) weeks, as they had to complete a minimum of 60% of tasks in a maximum of 14 weeks. However, students enrolled in 2013/14 started later (in the second week), and spent just 7.31 weeks on their IndiWork to complete an average of 50% of tasks, despite having 13 weeks to work on them. It is also interesting to note that the maximum duration was 104 days, which means that some students (n=60; 0.8% of the total student sample) continued working on the online tasks even after the course had ended. The reasons for these phenomena will be explored in the next paragraph.

Table 3: Key Indicators of IndiWork Activities

	Minimum		Maximum		Mean		Std. Deviation	
	2012/13	2013/14 & afterwards	2012/13	2013/14 & afterwards	2012/13	2013/14 & afterwards	2012/13	2013/14 & afterwards
IndiWork Total Score	0.0286	0.00	1.00	1.00	0.7432	0.620%	0.116	0.137
Total No. Attempts	1	1	21	28	11.20	13.38	1.764	2.880
Duration of IndiWork	0	0	98	96	62.69	51.18	17.429	22.244
Starting day (X days after the term starts)	-3	-3	82	89	10.62	15.03	10.472	15.156
Ending day (X days before the term ends)	-9	1	101	104	19.72	28.15	16.115	20.181

The results show that in a 13/14-week semester, students spread their IndiWork over eight weeks on average. This seems to suggest that students did not cram in the IndiWork just before the completion deadline at the end of the semester. In contrast, the average end day for IndiWork was in Week 10, which means that many students did less IndiWork in the final three weeks of the term. There are two possible explanations for this: that most students had already completed more than the minimum by Week 10, or that students were too busy with other assignments and courses at the end of the semester to focus on IndiWork. The cut-off effect addressed in the next section will provide more insights into this. Not all students, however, stopped in Week 10. As noted above, 0.8% of students (n=60) continued with IndiWork beyond the end of the semester, after their course grades had already been determined. This may reflect students' perception of the usefulness of the online learning part of the course. It is possible that this small percentage of students did not have time to complete all the tasks prior to the end of the semester as they were busy with other assignments. Thus, they may have wanted to resume their learning process during the semester breaks. Such strategic planning skills call to mind the 'self-control and self-regulation' described in Zhu, Au, and Yates (2016). It is also possible that students were not clear about certain concepts in academic writing while completing their coursework for core courses (e.g. how to format in-text citations for multiple citations). They then sought answers in these activities.

iii. Cut-off Effect

As students had the freedom to choose the activity type and sequence and when to do the activities, this section examines when students stopped doing online activities, to establish if there was any cut-off effect. Table 4 presents the completion details of IndiWork across cohorts. All activities are listed in the order they were presented to students, together with the mean score for each activity (note: scores have been rescaled between 0 and 1) and the corresponding cumulative IndiWork percentage. The second to last column, the attempt rate, refers to the percentage of students who attempted each activity. It should be emphasized that attempt rate here refers to the number of students rather than the number of attempts (which can be more than one per student). The last column simply provides the difference between the attempt rate of the activity shown on that row and that of the previous activity. For example, the mean scores in 2013/14 for the Pre-Unit 1 activity and Unit 1 activity were 0.93 and 0.95, respectively. If a student attained the mean scores in both activities, they would be awarded 0.0609 in total for their IndiWork. If a student managed to obtain the mean scores for each activity, by the time they had completed the Unit 3 activity on 'discursive essays/for and against essays', they would have attained 0.5502; that is, the minimum completion requirement for IndiWork for that year. The noteworthy point is that the attempt rate always showed the largest drop once the cumulative percentage had reached the minimum requirement; that is, 60% in 2012/13 and 50% in 2013/14 and 2014/15 (underlined in Table 4). Such a drop indicates that a certain number of students stopped doing IndiWork after attaining the minimum and this echoes the discussion above. The ongoing decrease in the attempt rate confirms that students stopped doing the activities rather than skipping particular activities. This suggests that there was a cut-off effect, as a clear majority of students stopped doing IndiWork once they had reached the minimum requirement.

Table 4: Completion Details of IndiWork across Cohorts

Activity	Mean	Cumulative IndiWork % Attained	Attempt Rate	Change in Attempt Rate
12/13				
Pre-Unit 1 Activities: IndiWork and CILL Quiz, updating your profile	0.93	2.15%	86.0%	---
Unit 1 academic style	0.88	9.44%	97.3%	+11.3%
Unit 1 precise words and hedging	0.89	13.19%	92.6%	-4.7%
Unit 2 what and why of referencing	0.9	20.15%	96.5%	+3.9%
Unit 2 referencing styles	0.9	24.07%	91.2%	-5.3%
Unit 2 in-text referencing	0.9	27.98%	82.9%	-8.2%
Unit 2 paraphrasing and summarising	0.96	31.89%	89.7%	+6.7%
Unit 3 writing problem-solution essays A	0.94	37.12%	97.2%	+7.6%
Unit 3 writing problem-solution essays B	0.93	43.44%	94.6%	-2.7%
Unit 3 paragraph coherence	0.98	49.43%	92.3%	-2.3%
Unit 3 discursive essays / for and against essays	0.92	55.80%	84.4%	-7.9%
Unit 3 revising your work	**0.89**	**60.88%**	72.9%	-11.5%
Unit 4 presentations - introductions and creating interest			56.8%	**-16.1%**
Unit 4 presentations - referencing, handover, and conclusions			50.1%	-6.7%
13/14				
Pre-Unit 1 Activities: IndiWork and CILL Quiz, updating your profile	0.93	2.17%	82.35%	---
Unit 1 academic style	0.95	6.09%	96.88%	+14.54%
Unit 1 precise words and hedging	0.89	9.88%	95.62%	-1.27%
Unit 2 what and why of referencing	0.95	13.15%	94.04%	-1.58%
Unit 2 plagiarism and information literacy	0.90	17.11%	92.85%	-1.19%

Activity	Mean	Cumulative IndiWork % Attained	Attempt Rate	Change in Attempt Rate
Unit 2 referencing styles	0.93	23.75%	90.62%	-2.23%
Unit 2 in-text referencing	0.91	27.76%	89.77%	-0.85%
Unit 2 paraphrasing and summarising	0.97	31.76%	85.92%	-3.85%
Unit 3 writing problem-solution essays A	0.91	36.89%	92.42%	+6.50%
Unit 3 essay introductions and paragraphs from sources	0.93	39.44%	86.85%	-5.58%
Unit 3 cause and effect verbs and conclusions	0.9	43.15%	82.85%	-4.00%
Unit 3 paragraph coherence	0.91	48.78%	75.19%	-7.65%
Unit 3 discursive essays / for and against essays	**0.89**	**55.02%**	64.42%	-10.77%
Unit 3 revising your work			52.46%	**-11.96%**
Unit 4 presentations - introductions and creating interest			49.23%	-3.23%
Unit 4 presentations - referencing, handover and conclusions			43.00%	-6.23%
Unit 4 presentations - Q and A and visual aids			36.46%	-6.54%
Unit 4 effective presentation delivery and body language			33.23%	-3.23%
14/15				
Pre-Unit 1 Activities: IndiWork and CILL Quiz, updating your profile	0.92	2.21%	72.83%	---
Unit 1 academic style	0.95	6.25%	93.87%	+21.04%
Unit 1 precise words and hedging	0.88	10.11%	92.22%	-1.64%
Unit 2 what and why of referencing	0.95	13.48%	88.25%	-3.97%
Unit 2 plagiarism and information literacy	0.89	17.51%	86.00%	-2.25%
Unit 2 referencing styles	0.93	24.36%	82.94%	-3.07%
Unit 2 in-text referencing	0.90	28.43%	81.30%	-1.64%
Unit 2 paraphrasing and summarising	0.96	32.51%	80.22%	-1.08%
Unit 3 writing problem-solution essays A	0.90	37.74%	91.10%	+10.89%
Unit 3 essay introductions and paragraphs from sources	0.92	40.34%	84.49%	-6.61%
Unit 3 cause and effect verbs and conclusions	0.89	44.12%	81.12%	-3.37%
Unit 3 paragraph coherence	**0.92**	**49.98%**	75.72%	-5.40%
Unit 3 discursive essays / for and against essays			63.50%	**-12.22%**
Unit 3 revising your work			54.64%	-8.86%
Unit 4 presentations – introductions and creating interest			49.37%	-5.27%
Unit 4 presentations – referencing, handover, and conclusions			44.58%	-4.79%
Unit 4 presentations – Q and A and visual aids			37.49%	-7.08%
Unit 4 effective presentation delivery and body language			31.92%	-5.57%

Unfortunately, this cut-off effect is not unusual in blended learning, CALL, or in learning science in general. The authors believe that this reflects the 'principle of minimal effort' suggested by Fischer (2007, p.419) and, similarly, the pragmatic approach suggested by other academics (Huon, et al., 2007). The only difference here is that, instead of seeking to obtain good marks, these students strove to meet the minimum requirement to avoid a penalty, as reported in previous studies. Worse still, under the current course design, students do not obtain extra marks in assessments for doing more, so they simply stop once they have met the requirement. A reason for concern might be that these students did not seem to consider whether they were stopping at an appropriate place in the series of online activities (i.e. making an informed decision to stop the learning process based on the course outline). These students simply stopped whenever they had reached the minimum (e.g. a language/referencing exercise in 2012/13, a content exercise in 2013/14, and an organization exercise in 2014/15). They therefore missed some essential concepts that course designers intended to introduce through these blended learning exercises. For example, most presentation-related IndiWork tasks had a low number of attempts across cohorts as they were post cut-off. Demonstrations of how to handle questions in a presentation (Unit 4, Activity 3: see https://youtu.be/y0dvug5rlD8) were thus neglected, and this has implications for the learning progress of students in completing their presentation assessment (Assessment 3). The findings here suggest that CALL designers should consider sequencing activities according to their importance instead of according to the learning sequence; this would ensure that all important activities are completed before the cut-off point. In other words, the course designers would have to estimate the cut-off point (e.g. Activity 5) and include essential activities prior to that point (thus requiring students to complete the essential activities) to increase the chance of students completing all or most of the essential activities.

In the light of the existence of a noticeable cut-off effect, when teachers design online curricula and activities, they should bear in mind the tendency of students to adopt the principle of minimal effort. In this case, the cut-off effect appears to be only related to students' perception of the availability of tasks. In fact, when applying the principle of minimal effort, students could have other considerations, such as the level of difficulty of a particular task, or the relevance of online tasks to assessments. Any of these factors can help students decide which online tasks to complete, and controlling these factors (e.g. availability of tasks) would allow teachers to manipulate the student online behaviours. The authors suggest that course designers consider the following: 1) setting a release date and end date for each online task that align with the classroom learning schedule, i.e., controlling the availability of tasks; 2) ranking tasks according to their level of relevance to assessments, i.e. showing the perceived impact of completing the tasks; (3) adopting an adaptive release mechanism whereby the next tasks are not released until the current tasks have been completed satisfactorily, i.e. controlling the availability and the order of tasks; (4) setting some tasks as compulsory and giving more weighting to these tasks, i.e. giving incentives to students to complete the online package at faster pace. Course designers can adopt these measures to influence students' online learning behaviour so that students attempt activities related to all the main learning outcomes before arriving at the cut-off point.

4.2 Predicting student outcome

To predict the overall course grade, eight independent variables were entered into the regression model. These variables were chosen because of their theoretical requirement (such as demographic factors and public exam scores as an indicator of language foundation) and the empirical correlation (scores of the first few IndiWork tasks). The adjusted R^2 of the model is 0.116 and f^2 is 0.1312 (small). This shows that the model can only predict a small portion of deviation of the overall course grade (Table 6a). Because the eight independent variables are significant predictors of overall course grade, it is worthwhile presenting these variables in a detailed manner. The total number of attempts at IndiWork can best predict the overall course grade (standardized $\beta = 0.139$, $p < 0.05$), followed by scores for IndiWork Unit 1 activities (standardized $B = 0.136$, $p < 0.05$), start day (standardized $\beta = -0.078$, $p < 0.05$), and scores for IndiWork Unit 2 general referencing activities (Table 6c). These four most influential elements are IndiWork-related factors, rather than demographic factors like public exam results. Apart from the strength of the regression coefficients, it is also interesting to note the net effect of certain variables on the predicted value of the regression equation. For every one-unit change (i.e. one attempt) in 'total number of attempts', there is a change of approximately 0.022 points to the overall course grade if the values of other independent variables are held constant. If students attempt activities (as an example) another 23 times, the overall course grade is predicted to increase by half a grade (e.g. C to C+).

Table 6a: Model Summary

Model Summary			
R	R Square	Adjusted R Square	Std. Error of the Estimate
.342	.117	.116	.4126

Table 6b: ANOVA Table

Model	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Regression	160.759	8	20.095	118.027	.000[i]
Residual	1216.825	7147	.170		
Total	1377.584	7155			

Table 6c: Regression Coefficients

	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
(Constant)	1.865	.034		55.349	.000
Total No. of Attempts	.022	.002	.139	11.151	.000
Start Day	-.002	.000	-.078	-5.057	.000
IndiWork – Unit 1 (Style)	.213	.020	.136	10.545	.000
DSE Level 4	.068	.011	.073	5.980	.000
IndiWork – Unit 2 (General Referencing)	.124	.020	.074	6.074	.000
End Day	.001	.000	.060	5.034	.000
Summer Semester (Yes = 1)	-.187	.040	-.053	-4.621	.000
IndiWork – Pre-Course Activities	.061	.017	.055	3.612	.000

The predictive power of blended learning activities on student outcomes was rather weak. The weak predictive power of the regression equation estimated in this study can be explained by the fact that only one, among many, of the academic skills can be noticeably enhanced through the blended learning environment (i.e. referencing skills), while other language skills need more practice to see obvious improvement, as discussed in the previous section.

Despite its focus on participatory variables (see Damianov, et al., 2009; Dawson, McWilliam and Tan, 2008), the previous literature has mainly focused on other effort-based participatory variables, such as course login frequency, reading course announcements, and access to course materials, but not the performance-based participatory variables in this study, such as scores in IndiWork. Perhaps future research can be conducted to explore the relationship between blended learning task performance (as performance-based participatory variables) and achievement of course outcomes.

The prediction equation established in this study can be useful for learning and teaching purposes. In particular, most predictors identified in this study can be obtained by the midterm, that is, with the scores of the first few IndiWork activities. This will allow student course performance to be predicted in the middle of the term, at-risk students to be identified early, and timely support to be provided to those students based on the course objective indicators. This corroborates previous studies, such as those by Klüsener and Fortenbacher (2015) and Essa and Ayad (2012), which discussed the benefits of learning analytics in identifying at-risk students.

4.2.1 Limitations

Although the researchers made every effort to ensure the quality of this study, there remain a number of limitations. First, although numerous studies have solely employed quantitative methods (e.g. Li, 2014), and although this learning analytics study can successfully identify certain trends and patterns such as the cut-off effect, which is the model for predicting students' outcome, more evidence from other data sources, for instance, using qualitative methods, could have been added to explain the patterns identified by this study. Second, as it was retrieved directly from the LMS database, the dataset for the current study was huge and it was not possible to thoroughly examine the problematic entries that were cleaned; it is also possible that some false negative entries were cleaned. In addition to the above methodological limitations, it is important to note that the cohorts and IndiWork tasks were not entirely comparable, because the course leaders made minor revisions to the content every year to improve the course. Furthermore, the whole blended learning design is the result of a major current reform in Hong Kong, and included a number of uncertainties and uncontrollable factors, e.g. the teacher's perception towards blended learning. Nevertheless, this study employed sufficient quality assurance measures and checking mechanisms to minimize these impacts.

5. Conclusion

This study aimed to explore students' online behaviours in the use of an online learning package and predict their outcomes with variables related to the package. The results indicate that students' pragmatic approach to the completion of online tasks can be manipulated by a more thorough consideration of student behaviour when designing online tasks, including their available dates, priorities, and restrictions in task selection. In this way, the cut-off point can be pre-determined by teachers to better achieve learning outcomes. Unfortunately, students' overall course grades were not well predicted by the online-activities-related variables, although the findings confirmed that a few performance-based blended learning indicators played a limited role in affecting the course grade. Future studies could attempt to combine blended tasks and other relevant external variables (e.g. demographic information) to establish a better model for blended learning courses, and consequently provide early indicators to enhance students' academic English skills. More structured tasks that focus on language can be inserted before the cut-off point to encourage a higher attempt rate and to allow the impact of such activities to be properly measured for course improvement.

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Appendix One. List of Activities for 2014-15 (Semester 2)

Units	**Components (No. of questions)**	Example (with details) of a component
Pre-Unit 1 **Deadline: 23:55 Tuesday 3 February, 2015**	Pre-Unit 1 Activities: IndiWork and CILL Quiz, updating your profile (17 points)	MC questions
Unit 1 **Deadline: 23:55 Tuesday 3 March, 2015**	Unit 1 IndiWork 1: academic style (30 points) Unit 1 IndiWork 2: precise words and hedging (31 points)	**Example of Unit 1 IndiWork 1: academic style** **Video Input:** https://www.youtube.com/watch?v=vfQFjFXRSkk **Exercise** Drag and Drop activity, on definitions of academic style issues (e.g. contraction) Labelling activity, identifying style problems of a paragraph Drag and Drop activity, on alternatives (i.e. fixing the academic style problems)
Unit 2 **Deadline: 23:55 Tuesday 3 March, 2015**	Unit 2 IndiWork 1: what and why of referencing (25 points) Unit 2 IndiWork 2: plagiarism and information literacy (32 points) Unit 2 IndiWork 3: referencing styles (52 points) Unit 2 IndiWork 4: in-text referencing (32 points) Unit 2 IndiWork 5: paraphrasing and summarising (30 points)	**Example of Unit 2 IndiWork 1** **Video Input 1:** https://www.youtube.com/watch?v=GOv1xz7ddGY **Video Input 2:** https://www.youtube.com/watch?v=46Tvl6fHODY MC questions on content presented in the videos
Unit 3 **Deadline: 23:55 Tuesday 31 March, 2015**	Unit 3 IndiWork 1: writing problem-solution essays (41 points) Unit 3 IndiWork 2: essay introductions and paragraphs from sources (20 points) Unit 3 IndiWork 3: cause and effect verbs and conclusions (30 points) Unit 3 IndiWork 4: paragraph coherence (45 points) Unit 3 IndiWork 5: for and against essays (34 points) Unit 3 IndiWork 6: revising your work (42 points)	**Example of Unit 3 IndiWork 1** **Video Input** https://www.youtube.com/watch?v=ezNC-EdIFt0 MC questions, on facts presented in videos, problems with Introduction paragraph, flow of an Introduction paragraph
Unit 4 **Deadline: 23:55 Saturday 18 April, 2015**	Unit 4 IndiWork 1: presentations - introductions and creating interest (22 points) Unit 4 IndiWork 2: presentations - referencing, handover and conclusions (36 points) Unit 4 IndiWork 3: presentations - Q and A and visual aids (19 points) Unit 4 IndiWork 4: effective presentation delivery and body language (27 points)	**Example of Unit 4 IndiWork 1** **Video Input 1** https://www.youtube.com/watch?v=Ze3IiHsHuIA MC questions / Drag and Drop activity, on contents presented in videos **Video Input 2** https://www.youtube.com/watch?v=BZTc6C4mrsg Labelling activity, on how to create interest