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The relationship between engaging in online course activities and final course grade in an online Psychology course

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Abstract

Online higher education is experiencing growth in enrolment and development which creates a need to continually evaluate the efficacy of online course delivery. Prior research reported that performance in online education is equivalent to traditional face-to-face delivery; however, minimal research exists to identify which elements of course design predict academic success. We aimed to identify which specific course components are predictors of (a) final course grade, (b) continuous assessment grade, and (c) major assessment grade in an online, undergraduate psychology course using data collated by the Learning Management System. We also addressed gaps in existing knowledge by exploring group differences within scores on significant predictors of course outcomes to determine whether these varied according to student characteristics. We found the number of times students visited the course site, viewed activities, and posted in activities significantly predicted students' final course grade, continuous assessment grades, and major assessment grades. The total variance explained by the regression models, was however, relatively low and therefore there may be additional factors not considered in the present study that may predict grades. We also found non-traditional, female, domestic students, enrolled part-time and in an online degree accessed the course site, viewed activities, and posted in activities significantly more frequently than their counterparts. Universities offering online courses should provide students with regular activities and opportunities to participate in course content to promote online learning and academic success.

Keywords: online; predictors; engagement; learning management system; academic outcomes.

Introduction

There has been significant growth in online university course enrolment, with the percentage of students undertaking one or more undergraduate class online in the United States rising from 15.6% in 2004 to 43.1% of to 2016 (Snyder, Brey and Dillow, 2019). In particular, the Covid-19 pandemic has led to a rapid increase in new course offerings (Sun, Tang and Zuo, 2020). Given the increase in demand and service provision, it is important to establish the efficacy of online course delivery.

Numerous studies have demonstrated that performance in online education is equivalent to, or better than, that of traditional face-to-face delivery. Chernish et al. (2005) assessed whether enrolment in a traditional (face-to-face) classroom, instructional television, or Internet-based classes had a significant impact on academic achievement over the course of one full semester. They found the delivery method did not contribute to significant differences in achievement. Neuhauser (2002) reported similar findings, with no significant differences in test scores, assignments, participation grades, and final grades between students enrolled in an online and face-to-face sections of a course. Interestingly, Neuhauser (2002) reported a slightly higher group average in these grades for online compared to face-to-face students. These results are further supported by the meta-analytic findings of Allen et al. (2004) who compared online and face-to-face groups and found online students outperformed traditional students. The evidence from these studies is clear: online provision of education is an effective method of achieving learning outcomes in tertiary education. Research that focuses on Open University courses in the United Kingdom has also highlighted the importance of considering learning analytics, both to implement an evidence-based framework to create and evaluate analytics in online courses (Rienties et al., 2016) and when training academic staff in online teaching practices (Macdonald and Poniatowska, 2011). However, few studies have attempted to tease apart which individual components of an online course foster student success in online study.

Learning analytic data are useful resources to determine how students interact with the learning management system and which factors may predict success in higher education. Learning analytics involve the collection and analysis of learner (i.e., student) data to better understand the learning experience and optimise the learning environment (Elias, 2011). Instructors report the benefits of using learning analytics include predicting student performance, identifying at risk students (e.g., students with low engagement), monitoring learning and progress, and raising awareness of unfavourable learning behaviours (Wong, 2017). In particular, interventions aimed at using predictive learning analytics to identify and support at-risk students have found that teachers can positively impact student performance when they utilise the data derived from learning analytics (Herodotou et al., 2019). However, the current evidence is limited in that learning analytic data have primarily focussed on face-to-face education as opposed to open and distance education (Wong, 2017).

It is widely reported that class attendance at university is related to academic success in a face-to-face context, with students who attend class on a regular basis achieving higher grades than those who do not attend regularly (Credé, Roch and Kieszczynka, 2010). In an online learning environment without dedicated classes, this would be analogous to the number of times an online student viewed the content pages on the course site. Studies have reported a positive association between time spent online and final grade in the course (e.g., Ryabov, 2012). Beyond the time spent online, the evidence becomes limited and varied. Some studies have measured individual components such as interaction with online forums and found students who interacted with online forums had better course outcomes than those who did not (Cheng et al., 2011). However, other studies report findings which dispute this. For example, Davies and Graff (2005) found greater online interaction did not lead to significantly higher performance for students achieving passing grades; however, students who failed in their courses tended to interact less frequently.

Few studies have attempted to tease apart multiple individual components of course design to identify the most important predictors of academic success. Of these, Ramos and Yudko (2008) found total page hits, defined as the frequency in which each student viewed the content pages at the class site, predicted students' total score on all exams given during the course. Further, participation in discussion (viewing or posting on course forums) had little to no effect on performance as measured by outcome on exams. Further, Nieuwoudt (2020) found a significant relationship between academic success and the number of hours students participated in and interacted with the online learning system; however, findings between courses were inconsistent as to whether watching the recordings of the virtual classes was associated with improved course performance.

There are a few limitations in the online education and learning analytic literature that we will aim to address. Firstly, the format of online delivery varies within the literature, with only a small number of cases reporting data on courses that were delivered 100% online (Misopoulos, Argyropoulou and Tzavara, 2018). It is also a commonly cited limitation of learning analytic research that the findings may be educational culture-specific and not applicable in other settings (Leitner, Khalil and Ebner, 2017). The present study aims to address these gaps in the literature by identifying which specific course components are predictors of course outcomes using data collated by the Learning Management System in a course that was delivered 100% online. Further, there has been a paucity of focus on predicting student success, with many researchers instead opting to monitor or measure learner progress (Yanosky and Arroway, 2015). Given this, variables such as self-selection of the mode of delivery or gender may need further exploration when comparing student performance as these factors may play a role in determining the success of online students (Misopoulos, Argyropoulou and Tzavara, 2018). Therefore, we also aim to explore group differences within scores on significant predictors of course outcomes to determine whether these varied according to student characteristics.

Method

Participants and procedure

Participants were undergraduate students (N = 455) enrolled in an introductory psychology course at an Australian online university. Participants ranged in age from 19-74 years (median = 27), with 409 domestic students and 46 international students. Ethics approval was obtained from the University ethics committee and participants were recruited by email. Participants were not required to do anything over and above the normal course requirements. Data were retrieved at the end of the study period by the researchers from usage information data provided by the Learning Management System (LMS). The University uses LearnOnline as its institutional LMS.

Measures

The following measures were selected based on available learning analytic data for the course. These data broadly align with the student-teacher, student-system, and student-

student interactions proposed by Agudo-Peregrina et al. (2014). Most interactions recorded were student-teacher which involved active participation in the form of posting and receiving feedback from the teaching team. Student-system interactions were recorded in course site visits and time spent watching lecture videos and student-student interactions were not directly assessed, although these occurred through interactions with forums and activities in which teachers participated as well.

Demographic data

Demographic data collated by the LMS included student age, programme enrolled in, gender, location, and study load. The following seven components were collected by the LMS and analysed in the present study:

- **Course site visits.** Course site visits were defined as the number of times in which a student logged into the course site.
- **Course forum views.** Course forum views were defined as the frequency in which each student viewed post(s) in a public forum from another student or teaching staff. Course forum posts typically included questions about the content or assessments and answers provided by the teaching staff.
- **Course forum posts.** Course forum posts were defined as the number of times in which each student posted content in a public discussion forum.
- **Activity views.** Activity views were defined as the number of times in which each student viewed post/s from another student or teaching staff in a weekly activity task.
- **Activity posts.** Activity posts were defined as the number of times in which each student posted content in a weekly activity task.
- **Announcement views.** Announcement views were defined as the number of times in which each student viewed dedicated post(s) from the course instructor. Announcement posts typically included content such as assessment information, submission deadline reminders, strategies for success when engaging with course content.
- **Time spent watching lecture videos.** Time spent watching lecture videos was measured as the total number of minutes a student spent watching lecture recordings.

The following three outcomes were collected by the LMS and analysed in the present study:

- **Final course grade.** Students' final course grade was calculated as the weighted average of five continuous assessment quizzes (weighted at 12% per assessment), as well as two written assessments (weighted at 10% and 30%).
- **Continuous assessment grade.** Students' continuous assessment grade was calculated as the weighted average of 5 quiz assessments. Each quiz was equally weighted for a total contribution of 60% towards the final course grade.
- **Major assessment grade.** Students' major assessment grade was calculated as the weighted average of an essay plan and an essay assessment. The essay plan was weighted at 10% and the essay weighted at 30% for a total contribution of 40% towards the final course grade.

Online course: Psychology Concepts

Psychology Concepts is an introductory course offered to students enrolled in psychology degrees as well as those who are enrolled in non-psychology degrees who may elect to enrol in the course as an elective. The course is open to students who are enrolled in a 100% online degree as well as those enrolled in an on-campus degree who may choose to study an online course within their degree. The course was delivered 100% online in a 10-week period from October to December in 2020. Each week covered a different introductory psychology concept including lifespan development, learning, personality, and clinical and abnormal psychology. Each topic in the course was presented in a series of three to four webpages consisting of written text, video lectures, and links to relevant electronic readings and internet resources. Students logged into the course site and engaged with materials by working through the weekly course content and participating in non-graded forum activities related to the weekly content that they could post in to receive feedback from the teaching team and their peers about their critical inquiry. This study analysed data relating to time spent watching lectures and engagement in activity forums, not data relating to the other resources such as readings as these interactions were not logged via the LMS. There were no tutorial classes nor any practical components that the students were required to attend. The assessments included five multiple choice quizzes, an essay plan, and an essay.

Data analyses

Data were analysed using SPSS version 26. Initially bivariate correlations between the individual online activities and student grade were calculated. Variables with a significant correlation with the outcomes were then entered into the regression models to determine the significance as well as the amount of variance associated with each significant variable. This is a similar methodology to that used by Zacharis (2015). Separate multiple regression analyses were conducted for the following outcomes: (a) final course grade, (b) quiz assessment grade, and (c) written assessment grade. Two outliers were transformed to the next highest values for participants who had extreme course site visit values as to retain their position within the data set. Further exploratory analyses were performed with a series of independent samples *t*-tests to explore whether group differences were present in the significant predictors from the regression models depending on gender (male or female), age (traditional or non-traditional), degree delivery format (online degree or on-campus degree), enrolment type (domestic or international), course enrolment (core or elective), or study load (full-time or part-time).

Results

Sample characteristics

Most participants were female (80.4%), domestic students located in Australia (89.9%), and enrolled in full-time study (58.2%). Roughly equal numbers of students were enrolled in an online degree and an on-campus degree (50.3% enrolled on-campus), with the most common programmes being Bachelor of Social Work (38.8%), Bachelor or Psychological Science and Sociology (20.4%), and Bachelor of Community Health (8.3%).

Relationships between activities and outcomes

Students' final course grade was significantly and positively correlated with all Learnonline components. Effect sizes ranged from small (number of times the student posted on the course forum) to large (number of course site visits: see Appendix 1).

Course components as predictors of course outcomes/student grades

Three multiple regression analyses were conducted to predict (a) final course grade, (b) quiz assessment grade, and (c) written assessment grade from course activities. The first regression to predict final course grade was significant, $F(7, 447) = 41.50$, $p = <.001$, with an R^2 of .39. We found that frequency of course site visits, activity views, and activity posts significantly predicted students' final course grade. The second regression to predict quiz assessment grades was significant, $F(7, 447) = 34.82$ $p = <.001$, with an R^2 of .35. We found that frequency of course site visits and activity views significantly predicted students' final course grade. The third regression to predict written assessment grade was significant, $F(7, 447) = 34.00$, $p = <.001$, with an R^2 of .35. We found that frequency of course site visits, activity views, and activity posts significantly predicted students' final course grade. See Appendix 2 for regression values and scatterplots with confidence and prediction intervals.

Group differences in engagement

Subsequent exploratory analyses were conducted to investigate potential differences in the three significant predictor variables from the regression models: course site visits, activity views, and activity posts. A clear trend emerged in the analyses of group differences in predictor variables. Online, non-traditional, female, domestic students, enrolled part-time accessed the course site, viewed activities, and posted in activities significantly more frequently than their on-campus enrolled, traditional, male, international student, full-time enrolled counterparts (see Appendix 3). Effect sizes ranged from small to moderate. No group differences in predictor variables were found between students who were required to enrol in the course as a core course within their programme or those who chose to enrol in the course as an elective course (see Appendix 3).

Discussion and conclusions

The aim of the present study was to determine whether specific course components were predictors of online course outcomes using data collated by the Learning Management System. We found the number of times students visited the course site, viewed activities, and posted in activities significantly predicted students' final course grade, continuous assessment grades, and major assessment grades. We also explored group differences within those predictors of academic success and found non-traditional, female, domestic students, enrolled part-time, in an online degree accessed the course site, viewed activities, and posted in activities significantly more frequently than their counterparts. We also found evidence that students enrolled in traditional on-campus degrees can be successful when enrolled in an online course.

Class attendance has been consistently associated with academic success at university (e.g., Credé, Roch and Kieszczynka, 2010) and researchers exploring online course enrolment have found a similar relationship between time spent online and course grades (e.g., Ryabov, 2012). Our findings support the growing body of literature in this space by identifying that the strongest predictor of course grades in an online course was the frequency of course site visits. This is particularly important in an asynchronous online environment where students are required to self-direct their own learning experience rather than being presented with a fixed timetable for classes or lectures. Given this, online educators in a tertiary environment should aim to promote drivers to regular course site access as well as reduce potential barriers to regular access.

Our findings have extended emerging research exploring the efficacy of individual components of course design. Engagement in activities demonstrated through both viewing and posting significantly predicted students' grade which demonstrated the benefits of an active learning environment for online students. This provides support for Nieuwoudt (2020) who also reported significant relationships between students' grades and posting as well as accessing the discussion board. Our findings have implications for future course design in online learning which should incorporate greater opportunities for students to engage in activities and receive feedback from teaching staff. The option to view and/or post in activity forums likely appeals to learners who enjoy the opportunity to post and actively receive feedback as well as those who prefer vicarious learning through observing the interaction of others in an activity forum (Nieuwoudt, 2018). The quality of the interaction is also important as engagement may be increased by including opportunities to learn in multiple ways through varied activities, and opportunities should be provided to engage with information in various ways (Biggs and Tang, 2007; Hattie, 2012). We also note that the beta coefficients for activity views in the regression models were negative, which may be reflective of the manner in which the different student groups interacted with this online learning platform and their level of experience within their degree. For example, students enrolled in an on-campus degree who elected to enrol in the online course engaged in less online activities, and hence viewed activities significantly less than online students, but performed better in their final course grade than those students enrolled in a 100% online degree. This may be due to a difference in study strategies in which on-campus enrolled students are not typically presented with the same opportunities for online engagement whereas students enrolled in a 100% online degree are typically expected to regularly engage in all online activities. Further research is recommended to better understand the study strategies of students who enrol in online courses as a single enrolment and whether these differ between the different cohorts.

Demographic differences in the predictor variables provide guidance on the patterns of course engagement. These findings are particularly useful for creating a profile of students who may need further support or encouragement to participate in visiting the course site or engaging with activities. Non-traditional students engaged in activities more often than traditional students which demonstrates that providing non-traditional students with a flexible learning environment may promote engagement as it mitigates the challenges commonly experienced by non-traditional learners such as work conflict (Kohler Giancola, Grawitch, and Borchert, 2009) or family (Meehan and Negy, 2003). Further, part-time enrolled students also engaged more frequently than full-time students which may indicate that a change to the traditional full-time study load expectations may facilitate engagement and course outcomes. Future research should aim to explore demographic differences in more depth, such as potential barriers or strategies to encourage engagement in online activity forums. For example, future research could explore international students' experiences to determine which online supports may be needed to assist international students in engaging more frequently with course materials online as this was a significant predictor of academic success in the present study. Further, this current study did not obtain data pertaining to the students' prior experience in online or blended education, which could be another potential influencing factor.

The findings in the present study provide a foundation for understanding the way in which online students interact with the learning environment and how this may affect academic performance. The Open University UK developed the Analytics4Action Evaluation Framework (Rienties et al., 2016), using which our findings broadly align with phase one, *reviewing key learning analytics metrics*. The Analytics4Action Evaluation Framework proposes that such findings should be translated into response actions, determining protocols, outcome analysis and evaluation, sharing evidence, and finally building strategic insight. Our findings could be used to inform specific actions to improve the learning environment and student support. Recommended response actions for teachers include facilitating more critical discourse by including regular non-graded forum activities in the weekly content, organising additional video sessions to drive more regular access to the course site and promote teacher engagement, and providing summaries of activity responses to encourage easier viewing of the discourse within activities or assessments.

Interpretation of the findings in the present study should be made in consideration of the following limitations. The prediction intervals found in the study highlight that future observations of individual students may vary, which could be due to individual differences (e.g., previous experience, personality, aptitude for different types of assessment) that were not accessed in the current study. While course site visits were the strongest predictor of course success, the measurement of course site visits was limited to frequency rather than duration of site visits. Future research could explore whether students who access the course site less frequently are doing so due to a lengthier visit duration as quality of visit may predict course outcomes in a different manner to quantity. It should also be noted that the total variance explained by the regression models was relatively low which indicated there may be other factors involved in the relationship between the course design elements used as predictors in this study and the outcomes. For example, while the number of predictors included was a strength of the present study, we did not have access to data for textbook usage or attendance of optional Zoom discussions with the teaching team which were offered regularly to students throughout the course. Further, the present cohort were enrolled in an undergraduate psychology course and future exploration of multiple courses or courses across disciplines would provide a more comprehensive understanding of the predictors of academic success in an online course.

A final consideration when interpreting recommendations for online learning is the ethical collection of student data and the responsibility to act upon learning analytic data. Learning analytics enable strategic decision making to develop a learning environment designed to support student success; however, it is important to note that these data may be incomplete in describing the student experience (Prinsloo and Slade, 2017). For example, the decision of what to measure is often guided by what we as educators' value (Knight and Buckingham Shum, 2017). Simply knowing more about a student group does not always translate into more appropriate action (Prinsloo and Slade, 2017). This raises a call to action in that institutions and practitioners must act upon these student data. A common practice that achieves this is to contact the at-risk students with personalised support tailored to their learning concerns which has demonstrated effectiveness in prior research including improved Grade Point Average, retention, and graduation rate (Wong, 2017). Therefore, using these data for predictive purposes to identify at-risk students and provide more customised support will enable pre-emptive action for practitioners to improve learner outcomes as opposed to being responsive after-the-fact.

Overall, engagement in course site visits, viewing activities, and posting in activities significantly predicted students' final course grade, quiz grades, and written grades in an undergraduate, online psychology course. Tertiary institutions providing online courses should aim to provide students with regular activities and opportunities to engage with the course content to facilitate learning and promote academic success online.

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Appendices

Appendix A

Table 1. Bivariate relationships between course activities and final grade.

Measure	M	SD	1	2	3	4	5	6	7	8
1. Course Grade*	58.34	24.70	-	.61**	.36**	.40**	.29**	.19**	.29**	.40**
2. Course Site Visits	73.10	51.23		-	.70**	.63**	.63**	.44**	.57**	.65**
3. Activity Views	60.67	81.56			-	.81**	.53**	.33**	.51**	.47**
4. Activity Posts	7.16	8.16				-	.32**	.29**	.36**	.44**
5. Course Forum Views	10.26	22.95					-	.63**	.59**	.30**
6. Course Forum Posts	0.71	2.52						-	.17**	.22**
7. Announcement Views	3.60	7.63							-	.34**
8. Time spent watching lecture videos	85.84	115.29								-

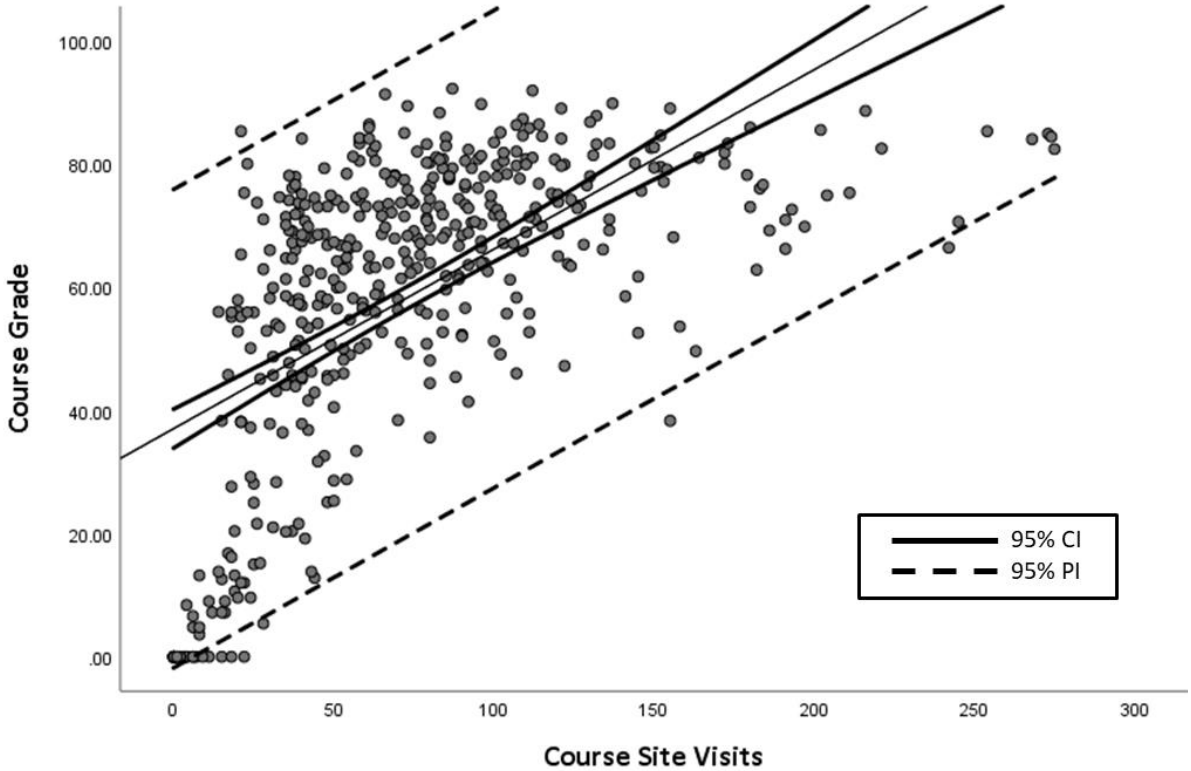
Note. M grade out of a possible 100 score. **Correlation is significant at the <.001 level (2-tailed).

Appendix B

Table 2. Linear model of predictors of students' final course grade.

Variable	b	SE B	β	P	95% CI
Constant	34.31	1.73		<.001	30.91, 37.71
Course Site Visits	0.35	0.03	.74	<.001	0.29, 0.42
Activity Views	-0.07	0.02	-.22	.004	-0.11, -0.02
Activity Posts	0.50	0.21	.16	.02	0.09, 0.90
Course Forum Views	-0.04	0.07	-.04	.52	-0.19, 0.10
Course Forum Posts	-0.71	0.51	-.07	.16	-1.71, 0.29
Announcement Views	-0.13	0.17	-.04	.45	-0.46, 0.20
Time spent watching lecture videos	-0.00	0.01	-.00	.96	-0.02, 0.02

Figure 1. Scatterplot of students' final course grade and course site visit scores with 95% confidence interval and 95% prediction interval.

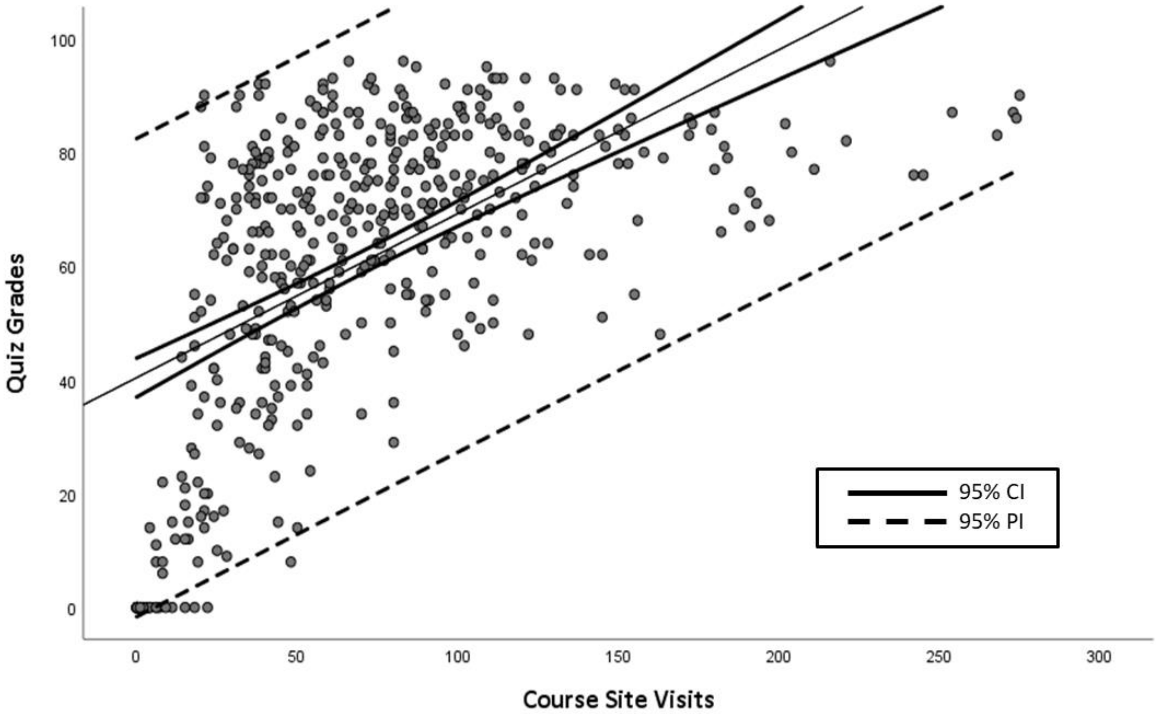


Note. CI = confidence interval. PI = prediction interval.

Table 3. Linear model of predictors of students' quiz grade.

Variable	b	SE B	β	p	95% CI
Constant	37.48	1.88		<.001	33.79, 41.17
Course Site Visits	.37	0.04	.73	<.001	0.30, 0.44
Activity Views	-0.06	0.02	-.20	.009	-0.11, -0.02
Activity Posts	0.40	0.22	.13	.08	-0.04, 0.83
Course Forum Views	-.08	0.08	-.07	.23	-0.24, 0.07
Course Forum Posts	-0.68	0.55	-.07	.22	-1.76, 0.40
Announcement Views	-0.07	0.18	-.02	.71	-0.43, 0.29
Time spent watching lecture videos	-0.00	0.01	-.00	.86	-0.02, 0.02

Figure 2. Scatterplot of students' quiz grade and course site visit scores with 95% confidence interval and 95% prediction interval.

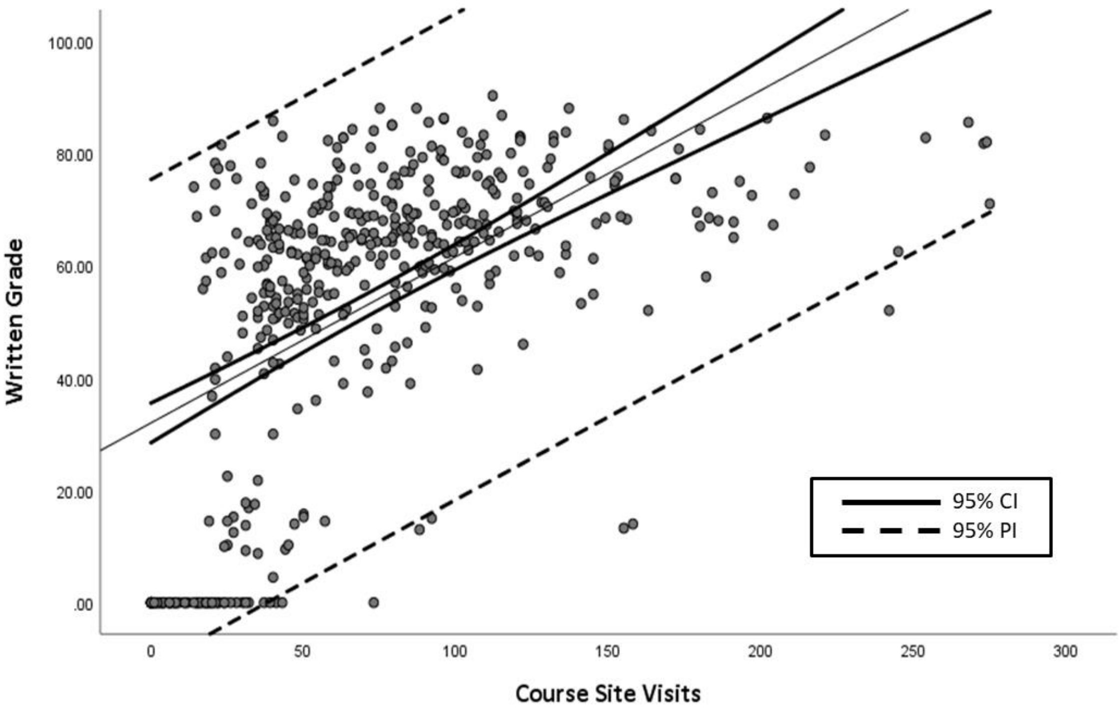


Note. CI = confidence interval. PI = prediction interval.

Table 4. Linear model of predictors of students' written assessment grade.

Variable	b	SE B	B	p	95% CI
Constant	29.56	1.94		<.001	25.74, 33.37
Course Site Visits	0.34	0.04	.65	<.001	0.26, 0.41
Activity Views	-0.07	0.03	-.21	.007	-0.12, -0.02
Activity Posts	0.65	0.23	.20	.005	0.20, 1.10
Course Forum Views	0.01	0.08	.01	.93	-0.15, 0.17
Course Forum Posts	-0.77	0.57	-.07	.18	-1.89, 0.35
Announcement Views	-0.22	0.19	-.06	.25	-0.59, 0.16
Time spent watching lecture videos	0.00	0.01	.01	.88	-0.02, 0.03

Figure 3. Scatterplot of students' written assessment grade and course site visit scores with 95% confidence interval and 95% prediction interval.



Note. CI = confidence interval. PI = prediction interval.

Appendix C

Table 5. Group differences in course site visits according to programme delivery, gender, age, location, study load, and enrolment choice.

Measure	M	SD	n	t	df	P	d
1. Programme Delivery				-5.33	342.73	<.001	0.50
Online	87.35	67.03	226				
On-Campus	60.44	35.80	229				
2. Gender				-2.08	452	.04	0.25
Male	62.65	51.93	88				
Female	76.18	55.52	366				
3. Age				-5.95	352.35	<.001	0.52
Traditional (18-21)	53.72	38.70	129				
Non-traditional (22+)	81.75	58.73	326				
4. Location				3.01	71.93	.004	0.33
Domestic	75.66	56.69	409				
International	57.33	36.63	46				
5. Study load				-4.85	275.56	<.001	0.50
Full-time	62.55	39.12	265				
Part-time	89.50	69.05	190				
6. Enrolment Choice				-0.56	453	.58	.07
Core course	73.07	57.21	361				
Elective course	76.64	47.07	94				

Note. The sample size for gender comparisons was 454 as one participant identified as indeterminate, intersex, or unspecified gender and was therefore removed from the male and female comparison.

Table 6. Group differences in activity views according to programme delivery, gender, age, location, study load, and enrolment choice.

Measure	M	SD	n	t	df	p	d
1. Programme Delivery				-6.03	346.41	<.001	0.57
Online	83.10	97.75	226				
On-Campus	38.54	53.16	229				
2. Gender				-3.30	147.34	.001	0.36
Male	36.89	70.92	88				
Female	65.51	81.40	366				
3. Age				-5.62	378.83	<.001	0.48
Traditional	33.39	54.42	129				
Non-traditional	71.47	88.07	326				
4. Location				5.88	88.77	<.001	0.56
Domestic	65.20	83.62	409				
International	20.46	43.37	46				
5. Study load				-5.83	249.04	<.001	0.62
Full-time	40.59	49.66	265				
Part-time	88.68	105.74	190				
6. Enrolment Choice				-0.83	453	.41	0.10
Core course	59.06	81.37	361				
Elective course	66.88	82.43	94				

Note. The sample size for gender comparisons was 454 as one participant identified as indeterminate, intersex, or unspecified gender and was therefore removed from the male and female comparison.

Table 7. Group differences in activity posts according to programme delivery, gender, age, location, study load, and enrolment choice.

Measure	M	SD	n	t	df	p	d
1. Programme Delivery				-5.65	387.07	<.001	0.53
Online	9.27	9.36	226				
On-Campus	5.07	6.12	229				
2. Gender				-4.60	172.86	<.001	0.46
Male	4.18	6.14	88				
Female	7.80	8.32	366				
3. Age				-5.12	307.71	<.001	0.47
Traditional	4.45	6.46	129				
Non-traditional	8.23	8.52	326				
4. Location				7.29	92.94	<.001	0.67
Domestic	7.70	8.33	409				
International	2.33	4.15	46				
5. Study load				-4.64	312.15	<.001	0.47
Full-time	5.60	6.56	265				
Part-time	9.33	9.58	190				
6. Enrolment Choice				-0.31	453	.75	0.04
Core course	7.10	8.16	361				
Elective course	7.39	8.21	94				

Note. The sample size for gender comparisons was 454 as one participant identified as indeterminate, intersex, or unspecified gender and was therefore removed from the male and female comparison.

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