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Students' engagement characteristics predict success and completion of online courses

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Abstract

This study examined students' engagement characteristics in online courses and their impact on academic achievements, trying to distinguish between course completers and noncompleters. Moreover, this research is intended to differentiate between those who pass the final exam and those who do not. Four online courses were examined with a similar pedagogical model (N_{students} = 646) using learning analytics methods. The results revealed significant differences between students who completed the courses and students who did not, in all 13 variables. Completers' learning activities were more than twice as high, except for writing in the forums. Course subject and ongoing task and assignment submissions predicted course completion, whereas, in addition to these variables, engagement with course materials and reading the forums predicted final exam success, as well. Thus, the prediction of success in final exam emphasized the significant importance of engagement in various activities in the online course.

KEYWORDS

achievement, higher education, instructional technologies, online course, student learning behaviour

1 | INTRODUCTION

In recent years, higher education institutions have been increasingly developing and offering online courses as part of their academic curriculum (Cohen & Soffer, 2015; Lee, 2016; Toven-Lindsey, Rhoads, & Lozano, 2015), providing access to a wide range of audiences and improving teaching and learning processes (Macfadyen & Dawson, 2010; Roby, Ashe, Singh, & Clark, 2013). However, along with the growing number of online courses, there is an increasing concern regarding the students' persistence and engagement, as well as high dropout rates, which reflected by very low activity (Kovanović et al., 2016) compared with face-to-face courses (Clay, Rowland, & Packard, 2009; Otter et al., 2013). The dropout rate of online courses stands at about 25-40%, whereas the dropout rate from academic courses, which are held on campus, is about 10-20% (Cohen, 2017; Cheng, Kulkarni, & Klemmer, 2013; Levy, 2007; Nistor & Neubauer, 2010; Park & Choi, 2009). Moreover, previous studies indicated that lack of persistence that is reflected in low engagement and poor selfregulation are important factors leading to attrition among students in online courses and inadequate academic achievements (Angelino, Williams, & Natvig, 2007; Otter et al., 2013; You, 2016). Therefore, it essential to better understand the ways in which higher engagement and self-regulation among online learners influence the learning and keep them motivated and participating in online course assignments.

In this context, the present study examined students' engagement characteristics in online courses and their impact on academic achievements, trying to distinguish between course completers and noncompleters. Engagement in this study was examined by a large scope of variables, which were derived from the students' activities during their learning process in the course. Specifically, 13 variables were divided into six main categories that portray the learning engagement in regard to the course subject, learning materials, interpersonal interaction, and assignments. Hence, students' engagement was explored by analyzing the learning management system (LMS) log files

using learning analytics methods. These methods enable us to find out about the learners' behaviour and understand its impact on learning persistence and online course completion. It should be noted that previous studies that used log files derived from LMSs were mainly concentrated on assessing students' activities in the online courses by measuring variables such as time spent in reading pages, number of content views, logins, video lecture views, as well as discussion forum participation (Kahan, Soffer, & Nachmias, 2017; Khalil & Ebner, 2017). However, there have rarely been studies that have used log file data to differentiate between students who complete a course compared with the noncompleters, trying to identify engagement characteristics that predict success or completion in online courses (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014; Ma, Han, Yang, & Cheng, 2015). Thus, the main goals of this study were to examine the differences in students' engagement by assessing those who have completed and those who have not completed the online course and to explore the variables that may predict success in online courses.

The results of this study contribute to a better understanding of the characteristics of students' activities in online courses, which is important for improving learning engagement and achievements as well as completing the course. Additionally, these results could also assist in evaluating the quality of online teaching and learning so as to design suitable academic online courses. This could lead to the implementation of support strategies for improving the quality of online learning (Ma et al., 2015).

2 | BACKGROUND

In recent years, the discourse around online academic courses being part of the curriculum for certification has renewed. Even though online courses are not a new phenomenon (Mason, 1998), a rapid growth in online academic courses has been seen recently in higher education instititions as part of their long-term strategies (Allen & Seaman, 2015). Higher education institutions are developing and offering online courses as part of their degree curriculums (Cohen & Soffer, 2015; Toven-Lindsey et al., 2015), providing access to a wide range of audiences, and improving teaching and learning processes (Macfadyen & Dawson, 2010; Roby et al., 2013). The considerations for developing online courses are broad and derived from efficiency, economic, organizational, pedagogical, and operational aspects (Bakia, Shear, Toyama, & Lasseter, 2012; Massengale & Vasquez, 2016).

In online courses, as in any academic work, students' active engagement affects their learning outcomes, cognitive development, and educational quality (Soffer & Nachmias, 2018; Hew, 2016; Smith, Sheppard, Johnson, & Johnson, 2005;). Previous studies discuss various aspects of engagement, for example, the effect of LMS design factors on user engagement (Zanjani, Edwards, Nykvist, & Geva, 2017); the influence of personal aspects on student engagement (Jung & Lee, 2018; Pellas, 2014); and instructor scaffolding for interaction (Cho & Cho, 2014). Yet hardly any have looked directly at the impact of the course's pedagogical model on engagement (Khan, Egbue, Palkie, & Madden, 2017). Furthermore, most of the previous research is primarily based on questionnaires or surveys. Only a

few have used student activity data, which are collected automatically in the LMS, to explore students' engagement.

2.1 | Students' engagement in online courses

Student engagement usually refers to the time and effort that students devote to their academic experiences (Ma et al., 2015). In previous research, it was found that students who had been actively engaged in their academic work showed a high of level learning outcomes. In other words, a significant relationship between active participation in online courses and academic performance was found (Hew, 2016; Macfadyen & Dawson, 2010; Romero, López, Luna, & Ventura, 2013). When exploring students' engagement in online courses, it is usually measured by students' activities in regard to three distinct strands: engagement with course learning materials, interpersonal interaction among instructors and students, and performance in tasks and assignments. In the next sections, we briefly describe the work conducted in each strand.

2.2 | Students' engagement with course learning materials

Online courses may offer an effective and enjoyable learning environment if they are designed properly, in a way that emphasizes interaction, clear structure, and strong content (Driscoll, Jicha, Hunt, Tichavsky, & Thompson, 2012). Online courses can take advantage of being able to offer course content through a wide range of up-todate and challenging web resources (e.g., text, audio, video lectures and presentation slides). Some researchers claim that students perceive the ease of access to varied, high quality, and up-to-date learning materials as benefiting their learning in an online course (Kahan et al., 2017; Palmer & Holt, 2010). Moreover, the course content is a significant driver in students' perception of the quality of the learning experience (Peltier, Schibrowsky, & Drago, 2007; Wu, 2016). In recent years, video is perceived as a rich and powerful medium (Chen & Sun, 2012; Ozan & Ozarslan, 2016; Zhang, Zhou, Briggs, & Nunamaker, 2006). Thus, a rich learning environment contributes to the effectiveness of online learning (Crawford-Ferre & Wiest, 2012) and enables more time to be dedicated to learning materials compared with classroom-based learning (Robertson, Grant, & Jackson, 2005). Furthermore, online learning provides more autonomy and enabling students to learn at their own pace. It allows flexibility in terms of time and location (Lim, 2016; Rodriguez, Rooms, & Montañez, 2008).

Online learning environments must foster engagement with learning materials (Sebastianelli & Tamimi, 2011). Organizing these resources into learning units seems to help students to manage their learning better and provides a clear and consistent structure that was found to be related to higher levels of student satisfaction (Kahan et al., 2017; Jones & Kelley, 2003; Paechter, Maier, & Macher, 2010).

2.3 | Interpersonal interaction in online courses

Communication is an important component in online courses, especially given the absence of physical meetings (Huang, Dasgupta, Ghosh, Manning, & Sanders, 2014). Through interpersonal interaction and information sharing, online courses enable collaborative learning and contribute to significant knowledge acquisition (Bell, 2011; Downes, 2007; Robinson, 2013; Siemens, 2014; Tee & Karney, 2010). The instructor usually initiates the forums and allows learners to join the discussions and interact on a variety of issues related to the subject (Akyol & Garrison, 2008; Chaturvedi, Goldwasser, & Daumé III, 2014). The learners are exposed to ideas, opinions, and comments from classmate. They contribute from their personal information as well as acquire knowledge created in the forums (Cacciamani, Cesareni, Martini, Ferrini, & Fujita, 2012). Moreover, instructor-student communication contains feedback regarding students' activities and performance, and can be used to answer questions regarding subject matter (Sebastianelli, Swift, & Tamimi, 2015).

Interpersonal interaction among students and instructors is strongly correlated with higher student engagement in a course (Dixson, 2012) and motivates them to succeed (Jaggars & Xu, 2013). This interaction has a significant and positive impact on student satisfaction (Marks, Sibley, & Sher, 2005; Toven-Lindsey et al., 2015), although the absence of proper communication might lead to a sense of isolation and a lack of sense of community (Song, Singleton, Hill, & Koh, 2004). Therefore, communication should be carefully designed to enable and promote interactions among instructors and students.

2.4 | Students' performance in online course assignments

Assessment of student knowledge and understanding of subject matter is used to promote learning and to ensure that students meet the intended learning outcomes. In online courses, assessment of learning processes becomes crucial especially in light of the fact that it serves as a means for increasing students' involvement and engagement with the course materials (Planar & Moya, 2016). Assessment tools assist the instructor in tracking and assessing students' knowledge in order to provide feedback. This feedback enables the students further guided engagement and the opportunity to revise the assignments (Cramp, 2011). Notably, feedback on assignments is important and must be given in a timely manner in order to keep the learners involved and motivated (Hattie & Timperley, 2007; Robertson et al., 2005).

Students in online courses are motivated when the instructors provide clear objectives and requirements (Toven-Lindsey et al., 2015) as well as specified assignments. Furthermore, it is essential to incorporate deadlines that are valuable to students when designing the course assignments. Deadlines help students avoid procrastination, encourage them to spend time on assignments, support them in self-regulation, and provide them with a context for regular contact with their instructor and peers (Graham, Cagiltay, Lim, Craner, & Duffy, 2001).

2.5 | Assessing student engagement through learning analytics

Student engagement with learning materials and activities during an online course are essential to the success of learning processes (Ma et al., 2015); thus, various methodologies for assessing student activity in these courses are developing. Some are based on online assignments, guizzes, and tests (Brooks, Thompson, & Teasley, 2015; Schiming, 2012). Some are based on learning analytics, which is the analysis of students' learning activity data that accumulates in real time in the weblog files of the LMS in which the fully online courses are offered (Blikstein, 2011: Broadbent & Poon, 2015: Goda et al., 2015; Johnson et al., 2013; McElroy & Lubich, 2013; Romero-Zaldivar, Pardo, Burgos, & Delgado Kloos, 2012). Hence, in recent years, we have witnessed the growing use of learning analytics as a popular method to analyse and assess students' behaviour and achievements in online courses (Kahan et al., 2017; You, 2016). Thus, the online learning environments, which use LMSs, enable the trace of students' activities with regard to self-regulated learning behaviour at any stage of a course's progression for the evaluation of learning processes and learner behaviour through formative as well as summative assessment. The collective data could assist in monitoring the students' behaviour and achievements during the online course, as well as identifying differences among students in order to detect and even predict dropout from the course (Cohen & Soffer, 2015; Lim, 2016).

Time and effort spent by students on online courses were found to be factors that affect their achievement (Ryabov, 2012). Accessibility of learning materials, presence of the instructor, timely instructor feedback, and the students' sense of community within an online course were identified as essential for effective online instruction (Cohen & Soffer, 2015; Roby et al., 2013; Romero et al., 2013; Zen, 2008). Thus, instructors may use the retrieved data and analyse it in order (a) to learn about student involvement and performance, (b) to improve instruction and assessment in real time, and (c) to adjust their teaching styles to student needs. In addition, learning analytics make it possible to track student usage of different parts of a website to have a better understanding of learning processes, their effectiveness, and their suitability for a learner.

Based on the research literature, an integrative research framework was developed in order to predict students' success and completion of an online academic course (Figure 1). The framework of the study includes 13 variables divided into six main categories that characterize the learning engagement as well as students' success and course completion. The learning engagement was measured by students' activities in the online course in regard to the course subject, learning materials, interpersonal interaction, and assignments (learning outcomes). Students' engagement was explored by analysing the LMS log files using learning analytics methods to predict success and course completion.

3 | THE STUDY AIMS AND QUESTIONS

Because student engagement in online courses is a strong predictor of student success and achievement of learning outcomes, the aims

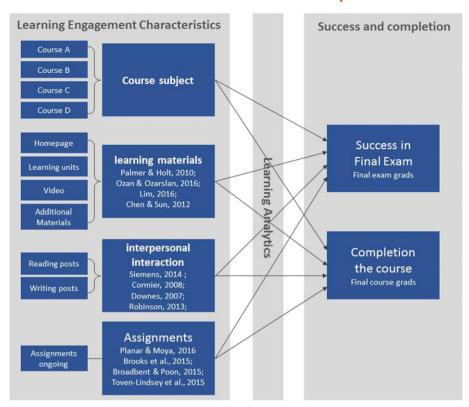


FIGURE 1 Research framework [Colour figure can be viewed at wileyonlinelibrary.com]

of this study are to explore the differences among students in regard to their engagement in academic online courses and to predict variables that have an effect on completion or noncompletion of a course. In this study, we distinguish between success on the final exam (grade) and completion of the course because of course completion depends on both the final exam grade and ongoing assignments throughout the course.

In order to achieve these research aims, three main questions were asked:

- Are there significant differences between students who completed and did not complete the course with regard to engagement with learning materials, interpersonal interaction, and assignments?
- 2. What are the students' online activities that predict success on the final exam?
- 3. What are the students' online activities that predict completion versus noncompletion of the course?

4 | METHOD

4.1 | Research Field

In the academic year 2013/2014, the university decided to implement a wide process of redesigning face-to-face courses into online courses. The present study examined four redesigned online courses (N = 646)

that were offered during the academic year 2015/2016. These courses are part of a special programme called "The Complementary Studies Program." The programme is intended for all undergraduate students at the university and offers them the opportunity to study subjects that interest them. The programme is mandatory for all undergraduate students on campus and requires each student to take at least three elected courses in fields that are polar opposite from their degree programme during their 3 years of studies. Thus, each course is characterized by a wide range of participants from various disciplines and from different academic years (within their Bachelor of Arts degree).

These four courses were selected because they were developed based on the same pedagogical model and unified structure. In addition, all four were semester-long courses, two credit hours each, and had a large number of students (>150).

Because instructors' course preparation is significantly and positively related to the students' viewing activities (Jaggars & Xu, 2013), a consistent instructional course model was designed and implemented as part of the online course development for each of the four courses, consisting of four main elements:

- Learning units that included 12 learning units that comprised the
 core of the online course materials. Each learning unit covered a
 different topic and consisted of a video lecture of the instructor,
 a summary of the lecture, reading/viewing materials (e.g., articles,
 original literary texts, and YouTube links), and assignments.
- Communication channels that included instructor-to-student discussion forums and student-to-student discussion forums.

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- Additional materials that were related to the course subject.
- General information about the course subject, its instructor, and guidelines regarding learning in an online course.

4.2 | Participants and design

The study included data from the online activity of undergraduate students (N = 646) who participated in the four online courses during the academic year 2015/2016. The four online courses were delivered on the Moodle LMS and were asynchronous. The first two courses were studied in the humanities faculty: course A in the field of East Asian studies; course B in the field of African studies. The third course, course C, in the History of the Gaze in the Arts was studied in the art faculty, and the fourth course subject, course D, the Cellular and Molecular Basis of Cancer, was studied in the medicine faculty.

Table 1 presents the frequency of students who participated in the online courses and their completion percentage: completed the course or not. A student did not complete the course if he/she did not have an average passing score for the ongoing assignments and final exam or did not attend the final exam. It should be noted that based on the course set-up, a student can complete the course even if he or she failed the final exam because the grade was composed of weighting the assignment scores with the final exam. The majority of students (74% on average) passed their course. In addition, as can be seen, although students did not finish courses A, B, and C mainly because they did not attend the final exam, the majority of students who did not finish course D failed the final exam. In order to compare the online activities of those students who completed the course and those students who did not complete the course, we merged students who did not have an average passing score for the ongoing assignments and final exam grade, with students who did not attend the final exam. This was due to the fact that students who did not attend the final exam did not complete the course.

4.3 | Measures

The present study included 13 variables that represented the students' activity in various elements of the courses (home page, learning units, video lectures, assignment submissions, and forums) and their course grades (assignments, final exam, and final course grade). Table 2 presents the study variables.

TABLE 1 Frequencies (%) of completers and noncompleters

	Completers (%)	Noncompleters (%)	Total
Course A	178 (85)	32 (15)	210
Course B	64 (74)	23 (26)	87
Course C	74 (67)	36 (33)	110
Course D	170 (71)	69 (29)	239

TABLE 2 The variables of the study

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Variable name	Variable description			
Students' activity				
Video activity in days	The number of days that the student used the videos in the course's website.			
Videos viewed (%)	The number of videos the student watched, divided by the number of videos that were presented in the course's website.			
Minutes of video viewed (%)	The number of minutes that the student watched the videos, divided by the length of the videos in number of minutes.			
Writing in forums	The number of times the student wrote messages in the forums, which represented an active involvement in the forums.			
Reading the forum posts	The number of times the student entered the forums, which represented a passive involvement in forums.			
Course homepage entries	The number of times the student entered the course's homepage.			
Learning unit entries	The number of times the student entered the learning units.			
Average unit page entries	The number of times the student entered a page in the learning units, divided by the total number of pages.			
Additional material entries	The number of times the student entered the course's additional materials.			
Assignments submitted (%)	The number of assignments the student submitted, divided by the number of assignments in the course.			
Total entries	The number of students' hits in the course website pages.			
Grades				
Assignments	Ranging from 0 to 100			
Final exam	Ranging from 0 to 100			
Final course grade	Ranging from 0 to 100			

4.4 | Procedure

The study was conducted using learning analytics and statistical methods. The data was collected from two sources: (a) the LMS, which included log files with student activities and online assignment scores; and (b) the exam grades and the final score in the course, which were provided manually by the instructors. Data mining was applied on a log data set, with over 188,510 records, where the LMS automatically documented the students' activity during the courses. After the courses ended, the data were retrieved and processed using SQL queries. Following that, functions were written in order to compute a set of variables, which described each student activity in the courses, in regard to course homepage, learning units, video lectures, assignment submissions, additional materials, and forums. Using SPSS-23, ANOVA analysis was applied to analyse the differences between completers and noncompleters in regard to engagement in the courses. In addition, two regression models were used to find the predictor variables for completion and final exam grades: (a) Logistic regression analysis was conducted in order to predict completion of the course based on online activity. Course subject was entered in the first block. Because the percentage of noncompletion was the lowest in course A, this course was selected as the reference category for the calculated dummy variable for course subject. (b) Hierarchical linear regression analysis was conducted in order to predict exam grades based on online activity, which represented students' engagement. This enables to control the effect of the course subject variable. In this analysis, all students who attended the exam were included (thus, grades may range from 0 to 100). In the first block, course subject was entered, this time with course D as the reference category because grades in this course were the lowest. It should be noted that prior to predicting students' exam grades, simple bivariate correlations were examined between students' exam grades and their online activity in their course.

5 | RESULTS

5.1 | Differences between students who completed and did not complete the course in regard to their online engagement

In order to examine the differences between students who completed the courses and students who did not complete the courses in regard to their online activities, eleven ANOVA analyses were conducted (one for each of the dependent variables, separately), with completion status (yes/no) and course subject as independent variables. Bonferroni adjustments to correct for 11 comparisons (p < 0.004) were used.

Results are presented in Table 3. As can be seen, students who completed their courses were highly engaged with the videos. They had more days of video activity, viewed a higher percentage of the videos, and had a higher percentage of video minutes viewed. In addition, they were highly engaged with other activities in their course. They entered their course homepage more, entered the learning units more, entered unit pages more times on average, and entered the additional materials more than students who did not complete their courses. Furthermore, they read the forum posts more (thus, they were more passively involved in forums). These differences were irrespective of course subject.

In regard to the rest of the activities, students who completed their course had more total entries and submitted more assignments than students who did not complete their course. However, these differences were found to depend on course subject (the interactions are presented in Figures 2 and 3, respectively). Specifically, Bonferroni post hoc comparisons indicated that this was the case in all courses (p < 0.001) except for course B (p = 0.11, p = 0.20, respectively).

Finally, regardless of whether or not students completed their course, differences were found between course subjects in the percentage of videos that were viewed, the percentage of video minutes that were viewed, students' passive involvement in forums, homepage entries, and additional material entries. Specifically, Bonferroni post hoc comparisons indicated that students in course A viewed a lower percentage of videos than students in courses B and C (p = 0.001, p = 0.003, respectively; M = 30.57, SD = 32.92, M = 46.06, SD = 33.79, M = 46.41, SD = 41.66, respectively). Similarly, students in course A also viewed a lower percentage of video minutes than students in courses B and C (p = 0.004, p = 0.01, respectively; M = 51.44, SD = 67.60, M = 84.99, SD = 96.14, M = 85.89, SD = 107.29, respectively). In addition, students in course C were more passively involved in forums than students in courses A, B, and D (ps < 0.001; M = 22.60, SD = 21.95, M = 10.72, SD = 12.79, M = 9.23, SD = 9.37, M = 7.45, SD = 10.93, respectively). Students in course B entered the homepage more times than students in course A (p = 0.001; M = 101.52, SD = 7.54, M = 65.75, SD = 6.03, respectively). Finally, students in course D entered the additional materials more times than students in courses B and C (ps < 0.001; M = 9.18, SD = 0.65, M = 1.39, SD = 1.11, M = 3.73, SD = 0.92, respectively), and students in course A entered the additional materials more times (M = 6.75, SD = 0.88) than students in course B (p = 0.001).

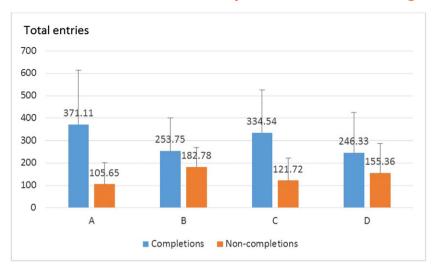
5.2 | Predicting completion versus noncompletion of the course, based on students' online activity

Logistic regression analysis was conducted in order to predict completion of the course based on online activity. Results indicated that both

TABLE 3 Means, standard deviations, and F statistics of the activity parameters, according to completion (yes/no) and course subject

	Completion		Noncompl	Noncompletion			
	М	SD	М	SD	F _(d.f) ¹	F _(d.f) ²	$F_{(d.f)}^3$
Video activity in days	7.42	7.04	2.99	3.12	55.21 _(1, 638) ***	1.18 _(3, 638)	1.48 _(3, 638)
Video views (%)	42.81	37.98	20.40	24.10	58.60 _(1, 638) ***	6.23 _(3, 638) ***	4.24 _(3, 638)
Minutes of video viewed (%)	73.95	87.46	39.00	78.18	22.15 _(1, 638) ***	5.48 _(3, 638) **	1.50 _(3, 638)
Writing in forums	0.18	0.83	0.04	0.35	4.57 _(1, 637)	0.83 _(3, 637)	0.26 _(3, 637)
Reading the forum posts	12.67	15.63	7.24	10.82	23.25 _(1, 637) ***	23.74 _(3, 637) ***	4.13 _(3, 637)
Course homepage entries	102.56	66.60	56.14	49.55	65.58 _(1, 637) ***	4.58 _(3, 637) **	4.25 _(3, 637)
Learning unit entries	34.60	48.55	11.79	13.94	23.24 _(1, 637) ***	2.98 _(3, 637)	3.11 _(3, 637)
Average unit page entries	1.26	1.43	0.42	0.71	39.20 _(1, 637) ***	0.25(3, 637)	2.06 _(3, 637)
Additional material entries	8.76	10.16	4.32	7.59	19.17 _(1, 637) ***	15.74 _(3, 637) ***	2.26 _(3, 637)
Total entries	306.44	210.28	142.02	115.47	75.31 _(1, 637) ***	1.08 _(3, 637)	7.03 _(3, 637) ***
Assignments submitted (%)	94.81	17.69	62.68	40.81	223.20 _(1, 638) ***	43.12 _(3, 638) ***	31.17 _(3, 638) ***

Note. $F_{(d,f)}^{-1}$ = main effect of completion (yes/no); $F_{(d,f)}^{-2}$ = main effect of course subject; $F_{(d,f)}^{-3}$ = an interaction effect of completion by course subject. *p < 0.05. **p < 0.01. ***p < 0.001.



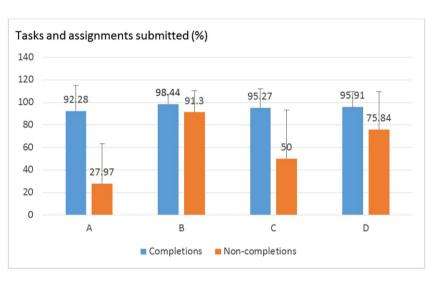


FIGURE 2 Completions and noncompletions by course subject interaction and total entries [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 3 Completions and noncompletions by course subject interaction and percentage of assignments submitted [Colour figure can be viewed at wileyonlinelibrary.com]

the first block, which included course subjects (dummy coded), and the second block, which included the activity variables, were significant, $\chi^2(3) = 18.15$, p < 0.001; $\chi^2(11) = 191.28$, p < 0.001, respectively. The final model that included both blocks was also significant, $\chi^2(14) = 209.43$, p < 0.001, Nagelkerke $R^2 = 0.415$ as presented in Table 4. As can be seen, course subject predicted completion, such that the chance to complete course A was higher than the chance to complete course B by 4.34, higher than the chance to complete course C by 4.31, and higher than the chance to complete course D by 3.01. Beyond course subject, the only other significant predictor of completion was percentage of assignments submitted, such that with each increase of 1 submitted assignment, the chance to complete the course increased by 1.03.

5.3 | Predicting students' exam grades, based on their online activity in the course

Simple bivariate correlations were examined between students' exam grades and their online activity in their course. It was found that students' exam grades were mostly low but positively related to most of the online activity variables: to percentage of assignments

submitted (r = 0.32, p < 0.001); video activity in days (r = 0.28, p < 0.001); video views in percentage (r = 0.21, p < 0.001); passive involvement in forums (r = 0.19, p < 0.001); course homepage visits (r = 0.25, p < 0.001); learning unit entries (r = 0.21, p < 0.001); average unit page entries (r = 0.22, p < 0.001); and total entries (r = 0.30, p < 0.001). Consequently, hierarchical linear regression analysis was conducted in order to predict exam grades based on online activity. The results indicated that the first block, which included the course subject (dummy coded), explained 20% of the variance in exam grades, F(3, 551) = 47.20, p < 0.001. The second block, which included the activity predictors, added 13% to the explained variance, $F_{\text{change}}(11, 540) = 9.36$, p < 0.001. The final model was significant and explained 33% of the variance, F(14, 540) = 19.16, p < 0.001. Table 5 presents the regression coefficients of the final model. As can be seen, the significant predictors of exam grades beyond course subject were reading the forum posts, course homepage entries, unit page entries, total entries, and percentage of assignments submitted. Specifically, the more students were passively involved in the course (read more forum posts), entered the course homepage more times, entered a unit page more times, and submitted more assignments, the higher their grade was on the exam. However, they had less total entries.

 TABLE 4
 Logistic regression for predicting completion versus noncompletion of the course, based on students' online activity

	D	S.F.	14/-14	F/D)
	В	SE	Wald	Exp(B)
Model 1:				
Course subject (A vs. B)	-0.744	0.316	5.543*	0.47
Course subject (A vs. C)	-1.027	.281	13.329***	0.35
Course subject (A vs. D)	-0.846	0.241	12.290***	0.42
Model 2:				
Course subject (A vs. B)	-1.15	0.51	8.24*	0.23
Course subject (A vs. C)	-1.46	0.46	10.13**	0.23
Course subject (A vs. D)	-1.10	0.41	7.32**	0.33
Video activity in days	0.05	0.05	1.16	1.05
Video views (%)	0.01	0.01	0.97	1.01
Minutes of video viewed (%)	-0.27	0.20	1.67	0.76
Writing in forums	0.33	0.33	0.97	1.39
Reading the forum posts	0.004	0.01	0.08	1.00
Course homepage entries	-0.01	0.01	2.69	0.99
Learning unit entries	0.003	0.01	0.03	1.00
Average unit page entries	-0.36	0.29	1.51	0.70
Additional material entries	-0.02	0.02	1.19	0.98
Total entries	0.01	0.005	3.42	1.01
Assignments submitted (%)	0.03	0.005	44.67***	1.03

Note. $R^2 = 0.042$ for Model 1, p < 0.001; $R^2 = 0.415$ for Model 2, p < 0.001.

6 | DISCUSSION

Students' engagement with the online courses and identification of their engagement characteristics are attracting increasing attention in the online learning environment (Sun & Rueda, 2012). Numerous

TABLE 5 Hierarchical linear regression for predicting exam grades, based on students' online activity

Course subject (A vs. D) 27.60 2.55 Course subject (B vs. D) 28.27 3.76 Course subject (C vs. D) 21.22 3.46 Model 2: Course subject (A vs. D) 31.23 3.08 Course subject (B vs. D) 24.09 3.91 Course subject (C vs. D) 17.38 3.87 Video activity in days 0.26 0.32 Video views (%) 0.001 0.06 Minutes of video viewed (%) 1.82 2.11 Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	
Course subject (B vs. D) 28.27 3.76 Course subject (C vs. D) 21.22 3.46 Model 2: Course subject (A vs. D) 31.23 3.08 Course subject (B vs. D) 24.09 3.91 Course subject (C vs. D) 17.38 3.87 Video activity in days 0.26 0.32 Video views (%) 0.001 0.06 Minutes of video viewed (%) 1.82 2.11 Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	β
Course subject (B vs. D) 28.27 3.76 Course subject (C vs. D) 21.22 3.46 Model 2: Course subject (A vs. D) 31.23 3.08 Course subject (B vs. D) 24.09 3.91 Course subject (C vs. D) 17.38 3.87 Video activity in days 0.26 0.32 Video views (%) 0.001 0.06 Minutes of video viewed (%) 1.82 2.11 Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	
Course subject (C vs. D) 21.22 3.46 Model 2: Course subject (A vs. D) 31.23 3.08 Course subject (B vs. D) 24.09 3.91 Course subject (C vs. D) 17.38 3.87 Video activity in days 0.26 0.32 Video views (%) 0.001 0.06 Minutes of video viewed (%) 1.82 2.11 Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	0.44***
Model 2: 31.23 3.08 Course subject (A vs. D) 24.09 3.91 Course subject (C vs. D) 17.38 3.87 Video activity in days 0.26 0.32 Video views (%) 0.001 0.06 Minutes of video viewed (%) 1.82 2.11 Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	0.30***
Course subject (A vs. D) 31.23 3.08 Course subject (B vs. D) 24.09 3.91 Course subject (C vs. D) 17.38 3.87 Video activity in days 0.26 0.32 Video views (%) 0.001 0.06 Minutes of video viewed (%) 1.82 2.11 Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	0.24***
Course subject (B vs. D) 24.09 3.91 Course subject (C vs. D) 17.38 3.87 Video activity in days 0.26 0.32 Video views (%) 0.001 0.06 Minutes of video viewed (%) 1.82 2.11 Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	
Course subject (C vs. D) 17.38 3.87 Video activity in days 0.26 0.32 Video views (%) 0.001 0.06 Minutes of video viewed (%) 1.82 2.11 Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	0.50***
Video activity in days 0.26 0.32 Video views (%) 0.001 0.06 Minutes of video viewed (%) 1.82 2.11 Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	0.26***
Video views (%) 0.001 0.06 Minutes of video viewed (%) 1.82 2.11 Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	0.20***
Minutes of video viewed (%) 1.82 2.11 Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	0.06
Writing in forums 0.10 1.35 Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	0.001
Reading the forum posts 0.19 0.09 Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	0.05
Course homepage entries 0.10 0.05 Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	0.003
Learning unit entries 0.08 0.04 Average unit page entries 4.72 1.98	0.10*
Average unit page entries 4.72 1.98	0.22*
	0.12
Additional material entries 0.11 0.14	0.22*
	0.04
Total entries -0.07 0.03	-0.53**
Assignments submitted (%) 0.39 0.05	0.30***

Note. Model 1: R^2 = 0.204, F(3, 554) = 47.197, p < 0.000; Model 2: R^2 = 0.33, F(14, 540) = 19.161, p < 0.000

studies have reported a significant relationship between active participation in online courses and academic performance (You, 2016). This active participation can be traced because students' learning behaviours are automatically recorded in the log files of the LMS, which has become common in most educational institutions. Thus, LMSs provide new opportunities for exploring students' learning participation progress and performance (Campbell, 2007).

The present study aimed to examine the learners' engagement characteristics in the online courses using learning analytics and their impact on academic outcomes, trying to distinguish between course completers and noncompleters. Moreover, the present study sought to differentiate between those who pass the final exam and those who do not.

6.1 │ Differences in students' engagement for completers and noncompleters

The findings indicated that there were significant differences between students who complete and do not complete their online course in most variables in the three distinct engagement strands: course learning materials, interpersonal interaction among instructors and students (reading the posts in the forums), and performance in tasks and assignments. In all of the strands, the completer's activities were more than twice as high, except for writing posts in the forums, which was very low and not found to be significant. These results are in line with previous studies that support the assumption that engagement with various course activities and time spent in study affects learning outcome and other outcome related behaviours

p < 0.05. p < 0.01. p < 0.001.

(Wu, 2016). Specifically, the findings of this research supply a comprehensive understanding of the type of engagement reflected in each student's online activity. With regard to course materials, in this research as well as in previous research (Goda et al., 2015), students who completed their course were highly engaged with the videos (Ozan & Ozarslan, 2016), learning unit resources, and additional materials and consistently submitted assignments (Lim, 2016). This corresponds to other study findings that demonstrated that students' late submission of assignments and frequency of course logins predicted their course achievement (You, 2016), although students' completion of learning assignments has a positive influence on their interaction in regard to learning (Ma et al., 2015).

Furthermore, significant differences were found between course subjects relative to students' engagement, regardless of whether or not they completed their course. Differences were found only in engagement with videos, additional materials, and reading posts in the forums. Possible reasons could stem form the difference in the characteristics of the content in each course, the relevance of the course materials, and the characteristics of each lecturer (Yukselturk & Bulut, 2007).

6.2 | Prediction of course completion and success on the final exam

With regard to learning engagement in the online course, which predicts completion of the course, the findings indicated that only the course subject and submission of the ongoing assignments were significant predictors of course completion. Furthermore, because the grade was composed of weighting the assignment scores with the final exam, it was important to explore the predictors that impacted the final exam. It was found that engagement with the course materials (average unit page entries, course homepage entries, and total entries), as well as engagement in the forums by reading the forum posts were significant predictors, as well as course discipline and assignment submissions, which were also found to be predictors of course completion. Therefore, the prediction of success in final grades emphasized the significant importance of engagement in various activities in the online course. Consequently, in online courses, we should focus on students' engagement with the course components and not on completion or noncompletion of the course. Notably, it was interesting to find that in the studied courses, interpersonal communication as well as engagement with video lectures (video views, video activity in days, and minutes of video viewed) were not found to be significant predictors of course completion and success on the final exam. These results are in contrast to previous studies, which centralized the importance of these activities as core elements in online courses (Agudo-Peregrina et al., 2014; Ozan & Ozarslan, 2016). Possible reasons could be that these activities were not obligatory and were not graded and that students used other communication channels (e.g., email and WhatsApp), which are external to the course website as well as video lecture summaries that are produced and distributed by the students.

7 | CONCLUSION

To conclude, this study provides essential information regarding engagement characteristics as demonstrated by the students' online activities. It also explores the differences between students who complete their course and those who do not, in all three dimensions of learning engagement as well as prediction variables for students' success on the final exam and completion of the online course. Although differences were found in all engagement characteristics (except for writing posts in forums), only the course subject and the submission of the assignments were found to be significant predictors of completion. With regard to the submission of assignments, it is not surprising because they are part of the final grade, as for course subject, it could be related to the differences in course characteristics, especially the clarity and relevance of course content. However, when the predictors of success on the final exam were analysed, the findings yielded other results and in addition to course subject and submission of assignments, engagement in regard to the interpersonal dimension (reading the forum posts) and with course materials were found to be predictors, as well, for success in an online course.

Understanding the differences between learners' engagement characteristics, as well as the variables, which predict success on the final exam, and completion of the course can assist in improving teaching and learning in online courses and reduce dropout. For example, empowering aspects of communication in the course for collaborative learning and learning acquisition (Cohen & Soffer, 2015; Kožuh et al., 2015), producing dedicated and helpful materials, and integrating suitable assignments along the course accompanied with instructor feedback. As mentioned in previous studies, the ability to understand the students' online learning activities and evaluate the quality of online teaching and learning is of great importance and assistance to the instructors in designing the online courses, as well as supporting their students (Robinson & Hullinger, 2008).

8 | LIMITATION AND FURTHER RESEARCH

Several possible limitations should be noted in the present study. First, despite the differences that were found between completers and noncompleters in learning engagement, conclusions regarding causality should be derived carefully and based on further research. The differences that were found can be explained by other things such as the differences between students in various characteristics. For example, students who completed their course may have had greater motivation and better technological orientation, which could have assisted them in their success and completion of their online course. In addition, differences in the instructors' characteristics may have biased results (e.g., personality, technological skills, and teaching strategy). These potential confounders require further investigation. Second, future research should examine a larger sample of courses from diverse disciplines and a heterogeneous student population. Third, the interpersonal communication (active writing in forums) in the online courses in the present study was relatively low and thus may have attenuated significant effect on learning completion and success.

Hence, future studies should explore other courses that are characterized with higher active communication.

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