JOURNAL OF LEARNING ANALYTICS

Volume 6(1), 34—53 . http://dx.doi.org/10.18608/jla.2019.61.3

Diversity of Online Behaviours Associated with Physical Attendance in Lectures

Amelia Brennan[1], Akshay Sharma[2], Pablo Munguia[3]

Abstract

A common use of technology in higher education is the provision of online course materials, invoking an investigation of the ways in which students engage with online course content, and how their participation changes over time. This is particularly necessary in the context of high absenteeism from lectures, where online access may be the only way in which particular students are engaging with the course. In this study, we examine large-scale patterns of attendance in class, as well as four types of access to online materials. We define two online behavioural metrics — richness and evenness — to capture the distribution of online behaviours within 255 courses, and examine how these change over time. We find that both physical and online attendance decrease throughout the semester, but the fraction of students present online is considerably higher than the fraction present in lectures. Students adapt their online behaviour, and rare behaviours disappear over time. It is important to consider how we provide content, both face-to-face and online, in order to ensure that as many students as possible are accessing this content in ways that we intend.

Notes for Practice

- Low attendance in lectures is common in higher education, and so students who are absent may be using online materials as an important source of course content. There are differences in the temporal patterns of student engagement with materials online and in lectures.
- This work finds that more students participate online than are present in lectures, but that the rates of both forms of attendance decrease over time.
- Students refine their online behaviour, and rare behaviours disappear over time.
- Instructors can use the methods described in this paper to assess how students engage with their course materials relative to our benchmarks, and to diagnose possible reasons that students disengage.

Keywords

Attendance, online engagement, online behaviour metrics, learning analytics.

Submitted: 15.06.2018 — **Accepted:** 08.10.2018 — **Published:** 15.04.2019

Corresponding author [1] Email: amelia.brennan@rmit.edu.au Address: RMIT Studios, RMIT University, Melbourne, Australia, 3000
[2] Address: RMIT Studios, RMIT University, Melbourne, Australia, 3000
[3] Address: RMIT Studios, RMIT University, Melbourne, Australia, 3000

1. Introduction

The use of technologies in education has intensified in the last decade, including diversification of online learning materials, accessibility of lecture recordings, and gamification of learning processes. Students can only participate in learning if they are present (Gump, 2006). However, thanks to developments in technology-enabled learning, presence is no longer limited to face-to-face interactions (Garrison, 2011; Wei & Chen, 2012). Face-to-face teaching is still a major education mode in many universities, and instructors have long been concerned that students may be replacing physical attendance in class with online learning (Weatherley, Grabe, & Arthur, 2003; Grabe 2005), also evidenced by myriad studies of the impact on attendance of online materials (e.g., Grabe, Christopherson, & Douglas, 2005; Grabe & Christopherson, 2005; Worthington & Levasseur, 2015; Khong, Dunn, Lim, & Yap, 2016; Barker, Hovey, Subhlok, & Tuna, 2014; Azab et al., 2016; Kinash, Knight, & McLean, 2015) as well as anecdotal reports from instructors. Many of these studies indicate that most students do not replace lecture attendance with access to online materials (Worthington & Levasseur, 2015; Khong et al., 2016; Barker et al., 2014; Azab et al., 2016), including a recent meta-analysis demonstrating that attendance in class is not negatively impacted by students having access to lecture recordings (Kinash et al., 2015). However, this is not the end of the story; with technology enabling the delivery of learning materials and the availability of data regarding the uptake of learning materials, we can now start investigating more closely the interaction between physical attendance and online engagement.

Low attendance in class is, in general, also of significant concern to instructors (e.g., Van Blerkom, 1992; Traphagan, Kucsera, & Kishi, 2010; Cohn & Johnson, 2006), and efforts to understand alternative motivations behind class attendance, and attempts to lift it, are often described in the literature (e.g., Dolnicar, Kaiser, Matus, & Vialle, 2009; Seary, James, & Conradie, 2014). Brennan, Peace, and Munguia (2018) used the average attendance patterns of hundreds of courses to demonstrate that attendance decreases over the period of a semester (outlined in further detail in the following section), and Hughes-Warrington (2015) reported a similar declining pattern in lectures. Stewart, Stott, and Nuttall (2011) observed the same decline over time in two courses, but with an increase again towards the end of the semester. The factors driving absenteeism can be external to the course — such as weather, travel time, or obligations to other courses — or internal, for example, the quality of the course (Brennan et al., 2018; Dolnicar et al., 2009; Khong et al., 2016).

Attendance is not necessarily equivalent to learning, and indeed many researchers have suggested that lectures are not always the best way to teach material, or to reach all students (Freeman et al., 2014; Kelly, 2012; Dolnicar et al., 2009). However, both face-to-face instruction and online material provision allow instructors to expose their students to course content in an intended manner, and in ways that align with their teaching pedagogy. In addition, some authors have suggested that blended online and face-to-face approaches can be more effective in combination than separately (Means, Toyama, Murphy, Bakia, & Jones, 2010; Bakia, Means, & Murphy, 2014; Bernard, Borokhovski, Schmid, Tamim, & Abrami, 2014). It is therefore important to provide feedback to those instructors regarding how their students are actually engaging with these two modes of teaching.

Thermal sensors, which record movement of people in and out of a room, offer a practical way to track occupancy in teaching spaces. Such sensors are used widely in industries around the world such as retail, transport, security, and leisure to measure footfall traffic. They have more recently been employed in higher education campuses to study learning space utilization and occupancy, and to improve efficiency of both space and energy use. When connected to a timetabling system, they can provide attendance data at a class level, enabling study of student attendance patterns and behaviour, from which considerable insight can still be obtained without requiring individual-level data.

Clickstream data is increasingly used to measure student usage of learning management systems (LMSs), and it is important to consider the ways in which students interact with online materials, and to understand when and how students are accessing the material. This is particularly true in the context of low physical attendance, when online access may be the only way in which particular students are engaging with the course. For example, Grabe (2005) found that 79% of students replaced lecture attendance with use of online lecture materials at least once, and almost 30% of those students did this at least six times. Similarly, Grabe and Christopherson (2005) found different patterns of access to online materials for students with different levels of class attendance. Even if access to online materials does not drive absence from lectures, the interaction between the two is worth studying.

The impact of time on the association between online activity and physical attendance has had limited treatment in the literature. Babb and Ross (2009) examined the timing of lecture slide availability on attendance among 175 students, finding that voluntary attendance was higher when the slides were available before the lecture, rather than afterwards. Stewart et al. (2011) examined the relationship between student attendance and online content access through the duration of a course, with 151 students in two geology courses over three years. They measured online access through both total “hits” recorded in the LMS, and the percentage of the cohort who accessed resources, and observed that while physical attendance declined through the semester, usage of online resources was driven by assessment periods; it appeared that students were engaging with the LMS the way they might occasionally access resources in the library, rather than as a regular supplement to weekly lectures.

We propose that focusing on *how* and *when* students use online materials within a course could lead to a better understanding of the relationship between online activity and physical attendance. This approach would allow a deeper understanding of how different types of materials and their architecture within the LMS may impact student engagement with those materials. There are many ways in which online behaviours can be constructed from online access data, particularly through clustering of usage patterns obtained from clickstream data (e.g., Amershi & Conati, 2010; Dutt, Aghabozrgi, Ismail, & Mahroeian, 2014; Mukala, Buijs, & Van Der Aalst, 2015). For example, studies on small courses have managed to dissect behaviours carefully and to assess specific tasks such as reading comprehension patterns in a course of 28 students (Peckham & McCalla, 2012). Massive open online courses (MOOCs) with thousands of enrolled students have paved the way in producing statistical approaches in understanding student behaviours stimulating the field of learning analytics (e.g., Kizilcec, Piech, & Schneider, 2013; Tseng, Tsao, Yu, Chan, & Lai, 2016; Anderson, Huttenlocher, Kleinberg, & Leskovec, 2014). For example, Kizilcec et al. (2013) studied the engagement in three computer science MOOCs of 94,000 students; they defined a set of four behaviours based on student participation each week, and then used *k*-means clustering to identify four main behavioural *patterns* over the duration of the course. Such studies generally examine a limited set of courses, in which all students are engaging within a particular online course structure. We are not aware of any studies of a large set of courses that examine common behavioural or attendance patterns over time.

Here, our aim is to link student online attendance and behavioural patterns with physical attendance in class. We ask three main research questions about course-level patterns and university-wide trends:

RQ1: How does attendance, both in class and online, change over the duration of a semester?
RQ2: Does student behaviour when engaging with online materials change over this same period?
RQ3: What is the distribution of behaviours?

Behaviours are defined according to relative amounts of access to content types (Figure 1, left). We analyze a large number of student enrollments (N = 34,158), in a large diversity of courses (N = 255). Given the scale of the study, we can expect noise in the patterns because of among-discipline differences; however, emerging patterns will lead to subsequent questions and a mechanistic understanding of the observed behaviours. We rely on two metrics that summarize the distribution of behaviours in a given course. Behavioural richness is a count of the various behaviours exhibited within a course; it tells us whether all students are behaving in the same way, or whether the course shell enables (and perhaps encourages) access to relevant content in multiple ways. Behavioural evenness measures the frequency of these behaviours: whether one or two behaviours dominate, or whether many behaviours are employed approximately equally within the cohort (Figure 1, right). With these two metrics, we are able to capture a range of behavioural distributions, and average these across courses to observe patterns that are consistent across all student cohorts.

We scaffold our work into three specific sections, to address the three research questions above and to understand the relationships between attendance and online behaviours. First, we analyze patterns of anonymous lecture attendance and online attendance for a large set of courses. Given the results of our earlier work (Brennan et al., 2018), that physical attendance dropped in all class types over the second semester of 2017, we expect physical attendance in lectures will decrease over the semester. However, we now also analyze online attendance, and test the null hypothesis that this form of attendance is constant irrespective of time in the semester. Second, we analyze online activity patterns associated with four different engagement methods: 1) browsing course content online, 2) downloading content, 3) reading discussion threads, and 4) accessing external applications (including to access videos and lecture recordings). Does student use of the different modes of participation vary in a course? Our null hypothesis is that, for a given course, use frequency across the four activities is similar; differences in usage frequency, particularly over time, would suggest different approaches to engaging with a course. The behavioural richness and evenness within a course are then compared among courses and across the semester to understand the common trends of behavioural distributions over time. Third, we compare changes in online behavioural richness and evenness with attendance patterns, both physical and online, to identify whether there are any associations between online behaviour measures and attendance. For example, if lecture attendance decreases, is there a corresponding increase in online participation, and are students maintaining their online behaviours over time? We explore further hypotheses that would help pave how pedagogical approaches such as blended learning can influence behavioural richness and evenness resulting in a better learning experience.

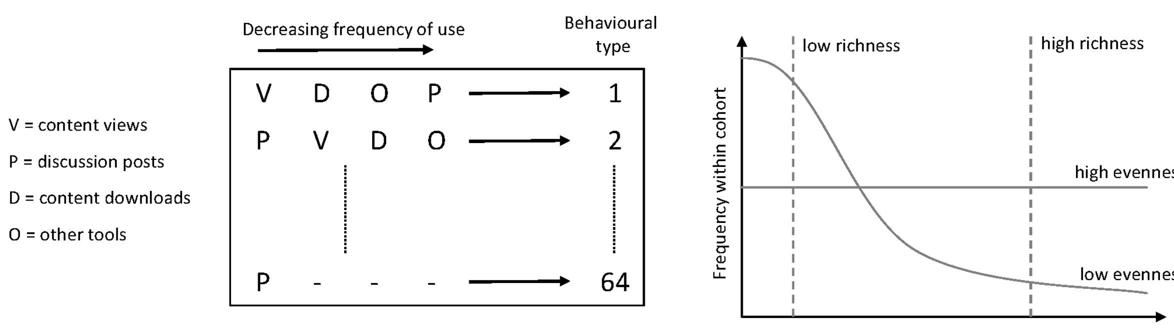

Figure 1: Analytical process defining behaviours (left) and possible distributions of behaviours (right) in the LMS. Note: In one undergraduate computer science course that was considered, the most common behaviour was to mostly view content, download some content, access just a handful of other available applications, and not look at discussions at all (denoted [V > D > O, –]). By comparison, the most common behaviour in a postgraduate business course was to mostly access other applications, and to view some content (denoted [O > V, –, –]).

In future, we hope that providing course-level data on attendance and online behaviours over time to instructors would allow them to better understand how students are engaging with their course, and lead to developments in how they structure their online and classroom teaching. The present study provides university-wide baselines for attendance and participation metrics, so that such data can be examined in context, and also so that "typical" student behaviours can be observed.

2. Initial Study

An initial study was performed in 2017, and was originally reported in Brennan et al. (2018); it is partially reproduced below, as an introduction to the extended work.

Thermal sensors were installed in early 2017 in 223 rooms around RMIT University, at campuses in Australia (n = 213) and Vietnam (n = 10). Previous physical space audits providing annual occupancy snapshots had identified rooms with historically low utilization, and these rooms were selected by Property Services for sensor deployment. The sensors are designed to sit above all entrances to a room, and use a thermal lens to detect the body heat of anyone passing underneath. As a result, they are strictly anonymous and do not record any attendance at an individual level. The sensors are able to count bi-directional movement, and provide an estimate of the room occupancy every 30 minutes by averaging the occupancy of shorter "resolution" time periods. The sensors also include a video lens, used for auditing during the calibration process, and following this process are expected to have an accuracy greater than 95%.

Occupancy data for semester 1 of 2017 were integrated with data from the university timetabling system, and so a database was constructed containing scheduled class, type of class, room capacity, and 30-minute timestamped occupancy. Since most classes have a duration greater than 30 minutes, the maximum reported measure during the booking duration was taken as the room occupancy for that entire booking. During this process, many "no-show" classes were identified, and certain extreme examples were immediately apparent, such as a practical class of 77 students where only twelve were expected to show up.

The thermal sensors were placed in rooms with capacities ranging from 10 to 350, so we investigated whether student attendance patterns were dependent on the size of the space. Figure 2a depicts summary plots of occupancy for all bookings, grouped into three-week blocks, for small (capacity < 50) and large (capacity ≥ 150) teaching spaces. Both room sizes display a significant decrease in occupancy over time: the median occupancy of small rooms decreased by one-third from the first quarter to the last quarter of the semester (Q1: median = 18, IQR = 12–24, n = 2774; Q4: median = 12, IQR = 8–17, n = 2761), while the largest rooms saw an almost 40% decrease in median occupancy over the same time period (Q1: median = 56, IQR = 38–76, n = 351; Q4: median = 34, IQR = 19–49, n = 413). In both cases, the statistical difference between the first and last quarters was highly significant (Kruskall-Wallis test, $P < 0.001$ in both cases).

a)

b)

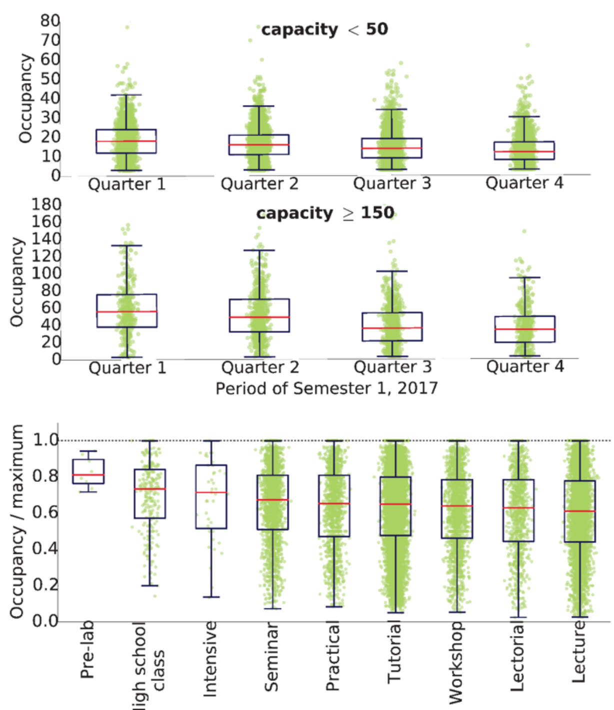

Figure 2: The changing occupancy over semester 1, 2017, for small and very large rooms (a), and the average occupancy (scaled by the maximum recorded attendance) for a variety of class-types (b).

These differences dependent on the room size may also indicate a dependence on activity type: larger rooms are more likely to contain lecture-type classes, in which students have less direct engagement, and often are able to access relevant material online in the form of lecture notes and recordings, whereas smaller rooms are more likely to host tutorial- or practical-style classes, where students are directly engaged in work and where material and/or personal assistance may not be accessible online. Alternatively, poor teaching in tutorials may be a more effective driver of student absence, particularly if they are able to attend alternative streams. We therefore classified attendance according to activity type, to assess the dependence level of physical attendance upon activity. Figure 2b summarizes the attendance of all bookings according to class type, where the maximum recorded occupancy of the semester was used as a proxy for class enrollments, and incorporated as an inverse scale factor. High-school classes[1] (median = 0.73, IQR = 0.57–0.84, n = 255) and short-term intensive classes (median = 0.71, IQR = 0.51–0.86, n = 43) had generally higher attendance, while lectures (median = 0.61, IQR = 0.44–0.78, n = 4730) and lectorials (median = 0.63, IQR = 0.44–0.79, n = 945) demonstrated the lowest average scaled occupancy.

The original work also included an investigation of the relationship between class attendance and student satisfaction with the course and with the teaching. That analysis found a small but significant positive correlation between the percentage of overall satisfied students and the average scaled attendance (r = 0.1, P < 0.05, n = 527; data were transformed to meet parametric assumptions). However, no correlation was observed between the percentage of students satisfied with the instructor and the average scaled attendance (r = 0.2, P = 0.12, n = 73). Notably, there were very few courses with low satisfaction and very high average attendance.

3. Methods

RMIT University currently has over 90,000 students enrolled, with the main campus located in Melbourne, Australia. In 2017 it initiated an LMS transition from Blackboard to Canvas, to be finalized in 2018. Canvas is an open source and transparent system that captures all student interactions with course material, and returns this data to the owner institution. This creates an opportunity to study the LMS dataset alongside other student participation data; in this case, the physical presence of students in classrooms. While the initial study examined the attendance patterns in a range of class-types, we restrict this new study to lectures only as, along with online materials, lectures are where students are most often exposed to the course content.

3.1. Datasets

Heat sensors collected additional room occupancy data in 228 rooms around RMIT University during February–May of 2018 (semester 1). These data were linked to the university timetabling system, to construct the specific attendance patterns of each course. In contrast to the initial study, the number of students enrolled in each lecture stream was also included in the dataset, to allow calculation of the lecture attendance each week as a fraction of total class size. Note that, in the case of large courses with multiple streams, the lecture class may be a subset of the online course shell, while in other cases, multiple courses may share a single lecture stream. (We treat the students present in a given class as a subset of students enrolled in that lecture stream but acknowledge that this does not account for students unofficially changing streams, or other non-enrolled students being present. However, we assume that these make up a small percentage of cases.

We selected 255 courses for analysis, with a total of more than 34,000 student enrollments (see Appendix). All of these courses were delivered over the period of 12 weeks, a standard long semester at RMIT. They were required to be higher education level, delivered face-to-face (with course materials available in the LMS) and with at least one lecture a week delivered in a room with a heat sensor installed (for physical attendance to be captured). The courses were required to have at least 10 students enrolled, and to have a minimum amount of student activity in the LMS, to ensure we weren't capturing "empty shells" that were not truly being used for a course. Further, we restricted the selection to lecture streams that took place on the same day of the week, at the same time and in the same location. Two public holidays were accounted for by allowing the attendance measure on those days to be null, rather than zero. If a lecture stream had zero attendees for more than one week, that stream was removed from the dataset under the assumption that these activities were regularly cancelled by the instructor, or were shifted to a different location, and that the zero attendance was due to external factors, rather than all students choosing not to attend. Of the initial set of 255 courses, 250 had exactly 12 weeks of attendance data for an associated lecture stream, and no more than one week with zero attendance.

Some courses had up to four lecture streams held in rooms with heat sensors installed, leading to a dataset containing 294 individual lecture streams (see Appendix). However, because heat sensor data does not identify students that attend a given lecture, we performed our analyses at the course level, considering each course as a population of students. In the final part of this work, where the online activity is linked to the physical attendance, we restricted the dataset to those courses where only a single lecture stream was recorded (n = 212), to avoid biasing the analysis towards those courses with several lecture streams.

[1] RMIT also offers Victorian Certificate of Education courses.

We aggregated data for each calendar week to enable among-course comparisons and because no classes were physically delivered over the weekend, even though there might be activity in the LMS. The Easter holiday (Thursday-to-Thursday) fell during the fifth week of the semester, therefore we averaged the online data of two calendar weeks (which included the holiday) to produce week 5 of the semester in our analyses. We also combined the lectures of Monday-to-Wednesday of the first calendar week, and of Thursday–Friday of the second, to create week 5 of physical attendance data.

3.2. Online Behavioural Patterns

Students are able to access their Canvas course shell either via the browser, or through the Canvas application, however these appear in the clickstream data in different ways. Between 75% and 90% of students considered used the browser exclusively each week, while between 12% and 22% of students used both the application and the browser each week. Further work is required to properly determine the ways in which those students who use both are doing so, however initial checks suggest that fewer than 5% of all students used the application more than they use the browser. In this analysis we considered only students who accessed the LMS via the browser, and assume they continued to do so throughout the duration of the course; we acknowledge this point as a minor limitation of the study.

We recorded student engagement with the LMS via a browser in one of four activities (Table 1) chosen to capture a range of meaningfully different operations. For a given student, the number of times they performed one of these activities (for example, each time they viewed a content webpage in the course LMS) was aggregated over the week, and the four activity types were then ranked in order of these frequencies. The order of the activity types defines a behaviour; a student could therefore be associated with one of 64 different potential behaviours in a given week (Figure 1, left). It should not be assumed that the activity types defined in Table 1 are the only options available to students, nor that they can be taken as a true representation of how students are choosing to engage with the content in all cases. However, they are varied enough to capture, at a cohort level, a clear set of different behaviours that can be examined across and between courses. In different weeks, a student could show different frequency patterns; however, in this analysis, we are only interested in population-level responses and the individual-level variation in behaviours will be presented elsewhere. While much of the variance in these behaviours is attributable to individual preferences (for example, whether a student is comfortable posting their opinion on a topic to the rest of the class), at least some of the variance may also be attributable to the structure of the course content in the online shell and the encouragement of certain behaviours over others, whether explicitly stated or by unconscious influence of the instructor.

Table 1: Four Activities Captured Within the LMS, and the Motivations for their Selection

Action	Description	Motivation
Content view	Access to content that is stored either as text on a web page, or as an embedded file rendered on the page; access to the course homepage was not included	Allows visibility of access to course content on a regular basis
Content download	Download of any file (excluding image files; see text)	Similar to content view, except students may download content once, and review it offline
Discussion view	Access to any discussion topic or subsequent entries	Demonstrates interest in peers' perceptions of the course content
Access external application	Access to any content provided through an external tool or application accessed through the Canvas course shell; this includes videos and lecture recordings	Encompasses a wide range of passive and active access to content

Individual student actions were dropped if they involved an image file, as images are downloaded and cached automatically in the rendering of a page, and so should not be considered additional actions since they are not separate actions from a viewing or downloading content. Note that only a relatively small subset of lecture streams were recorded, due to RMIT's opt-in policy, and that recordings and other videos were most commonly accessed through external applications.

The number and distribution of behaviours were captured by calculating the behavioural richness and behavioural evenness. Behavioural richness, R, is the number of different behaviours observed in a given course in a given week, and so is bounded between 1 and 64. This metric is biased towards rare behaviours as it only takes into account the presence or absence of behaviours. Behavioural evenness E, defined below, is instead biased towards common behaviours, as it takes into account the frequency of each of the 64 behaviours in a given week. High evenness represents behaviours having similar frequencies in a given week, and low evenness represents one or few dominant (highly frequent) behaviours (Figure 1, right). Behavioural evenness is defined for a given course in a given week as:

$$E = \frac{-\sum_i^n p_i \times \log_2(p_i)}{\log_2(n)}$$

where p_i is the fraction of the cohort that exhibit behaviour i, and n is the total number of behaviours present in that course in that week. Therefore, E is bounded between 0 and 1 (Magurran, 1988).

3.3. Data Analysis

First, we were interested in understanding how online and physical attendance varied through the semester. We used fractional attendance, the proportion of enrolled students present in a given week (whether online or physical), as our dependent variable. A student was considered present online if they engaged in one of the four activities considered in this study via the browser, so that visits to the landing page only were not included. A check of the broader definition of online presence, where students were counted if they accessed the course shell in any way including via the app, indicated that this online attendance was slightly higher, but followed a similar temporal pattern to that observed using the stricter definition. In order to compare differences between online and physical attendance, we used a mixed model where attendance type was a fixed factor and week of the semester was a random effect. Because week of the semester was able to explain a proportion of attendance variation, we then regressed each of the attendances against time. This method allowed us to obtain the variation in weekly attendance independent of time.

Next, we compared the participation patterns of the four online activities and how these differed throughout the semester. A mixed model tested differences among activities (as a fixed factor) taking into account week of the semester (as a random effect). Behavioural richness and evenness were then regressed against week of the semester. The residuals of these regressions were used to identify richness and evenness levels independent of the influence of week of semester.

We then explored the relationships between the online behavioural metrics and the two attendance modes. When considering the association with physical attendance, we limited the dataset to courses with a single captured lecture stream (n = 212), to avoid biasing toward courses with multiple lecture streams. We compared the richness and evenness against the online and physical modes of fractional attendance, and in each case regressed the residuals of the behavioural metric against the residuals of the attendance measure, to remove the effect of week of semester.

Finally, we explored whether students changed their online behaviour through the semester by comparing behaviours from weeks 2 and 11. We categorized students present online in week 2 according to their behaviours in that week: "rare" behaviours were defined as those in the bottom 25% of behaviours in a given course (approximately 10% of all students), ranked according to the number of students engaging in each, while the most common behaviour in the course was that with the highest number of students (approximately 20% of all students). We then compared how the two groups of students — common and rare — participated in week 11, whether they were still present online, and whether they were engaging in rare or non-rare behaviours.

4. Results

An average of 72.8% (S.D. = 7%) of enrolled students were active online at some point in the semester, and an average of 49.1% (11.3%) of students scheduled to be in the classroom were actually present. Online attendance was significantly greater than physical attendance throughout the semester ($F_{1,11} = 5$, $P < 0.01$), where time of the semester only explained 22% of the variance (Figure 3). However, physical attendance had a greater decline (slope = –0.030, F = 100.5, $r^2 = 0.90$, $P < 0.05$) than online attendance (slope = –0.014, F = 11.7, $r^2 = 0.49$, $P < 0.05$). A dip in online participation during week 5 was most likely due to the mid-semester holiday.

The level of engagement differed among the four activities ($F_{3,12} = 5$, $P < 0.001$; Figure 4), where viewing content had the greatest fraction of students to ever participate in this activity (59.9% ± 22.6%) followed by downloading content (56.6% ± 24%), viewing discussions (29.2% ± 19.4%), and accessing external applications (23.7% ± 19.6%; see Appendix).

The mean number of online behaviours (richness, R) was 17.1 (S.D. = 1.4) in a given course, out of a possible 64 behaviours. Further, richness decreased over the duration of the semester (slope = –0.35, F = 65.3, $r^2 = 0.85$, $P < 0.05$; Figure 5, left). In contrast, the mean evenness of behaviours (E) was 0.82 (0.01), indicating that the average distribution of behaviours showed some strong dominant behaviours, but with relatively equal distribution of students among behaviours. Evenness remained approximately constant across the weeks of the semester (slope = –0.002, F = 5.9, $r^2 = 0.30$, $P < 0.05$; Figure 5, right).

After removing the effect of week of semester, fractional attendance was positively associated with behavioural richness, explaining 47% of the variance (F = 10.8, $r^2 = 0.47$, $P < 0.01$; Figure 6, left). However, behavioural evenness was not associated with online attendance (Figure 6, right), but remained relatively constant as more students were active online (F = 2.8, $r^2 = 0.14$, P = 0.12).

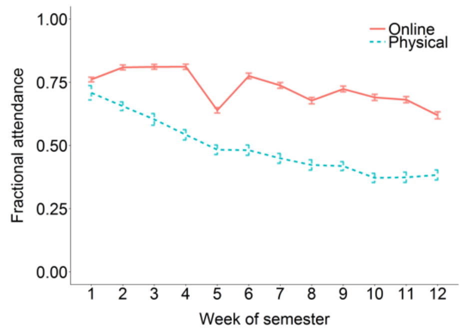

Figure 3: Average fractional attendance as a function of semester week for online (red solid line, n = 255) and physical (blue dashed line, n = 294) attendance modes. Note: Online attendance for week 5 is an average of two calendar weeks, which include both teaching and holiday periods; error bars = 1 S.E.

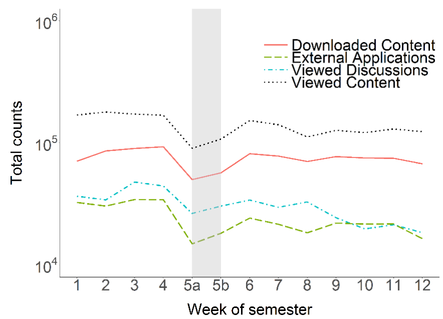

Figure 4: Access counts for each activity-type across all courses each week. The shaded region indicates the mid-semester break, which straddled two calendar weeks.

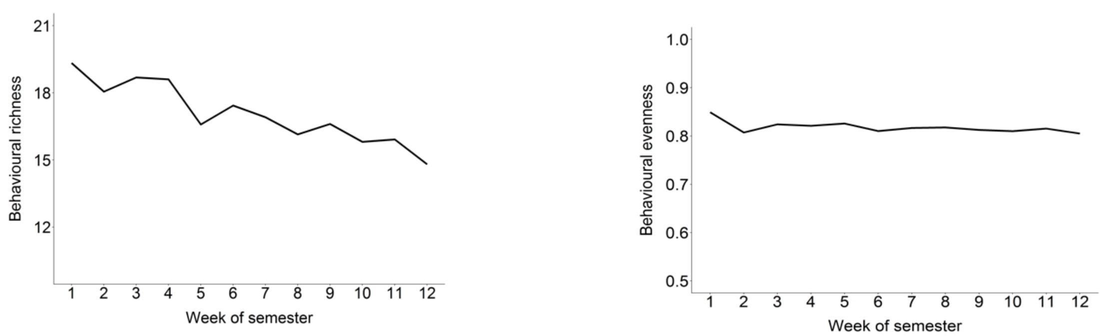

Figure 5: The online behavioural richness (left) and evenness (right), averaged across all courses, for each week of semester.

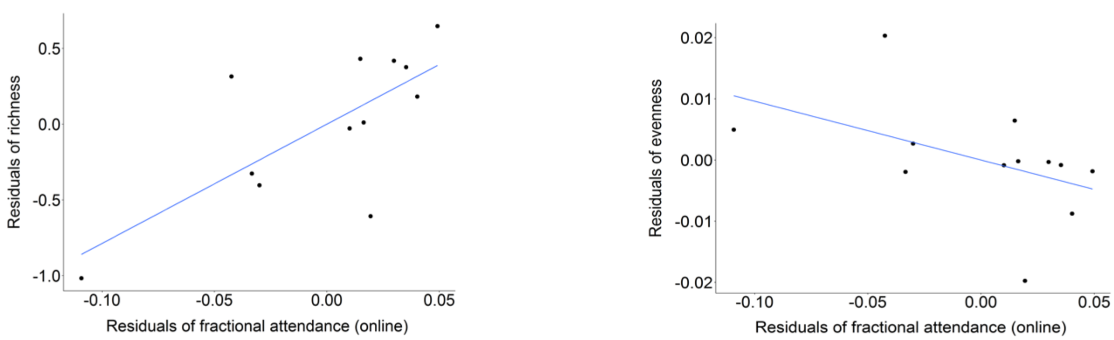

Figure 6: Residuals of behavioural richness (left) and evenness (right) associated with the residuals of online attendance. Note: Regressing residuals of these two variables removes the effects of time on either component; the slope in the right-hand plot is not significantly different from zero.

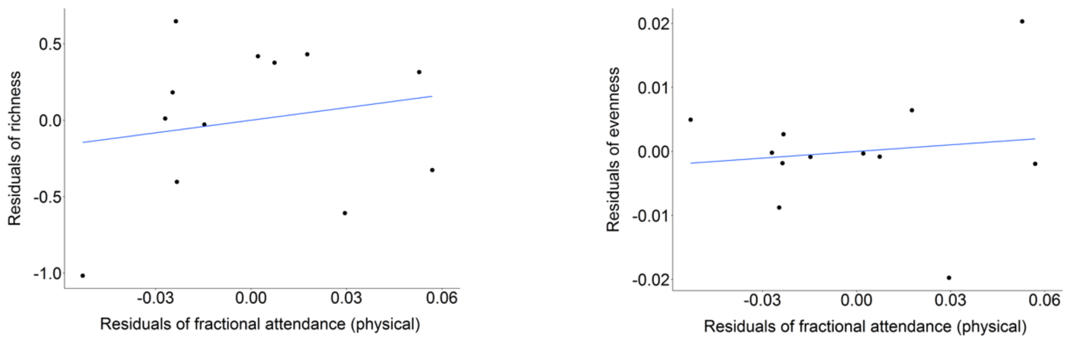

Figure 7: The residuals (after time effects are removed) of behavioural richness (left) and evenness (right) associated with the residuals of lecture attendance. Note: The slopes are not significantly different from zero.

Similarly, once the effects of time were removed, there was no significant association between richness and the fractional physical attendance (F = 0.36, r2 = 0.0, P = 0.56; Figure 7, left), or between evenness and the fractional physical attendance (F = 0.16, r2 = 0.0, P = 0.69; Figure 7, right).

The drop in richness over time was driven in part by students disengaging online, as well as by a shift from rare to common behaviours towards the end of the semester (Table 2). Students initially displaying rare or common behaviours in week 2 showed similar rates of disengagement in week 11. However, 11.5% of students shifted from common to rare behaviours; in contrast, 51.1% of students initially showing rare behaviours shifted to common behaviours.

Table 2: Students Classified in Week 2 and their Online State in Week 11

Online presence	Students in week 2, N	Offline in week 11	Rare behaviours in week 11	Non-rare behaviours in week 11
Week 2 rare-behaviour students	3,162	27.3%	21.5%	51.1%
Week 2 common-behaviour students	7,890	31.3%	11.5%	57.3%

Note: "Rare-behaviour" indicates any behaviour in the bottom 25% of behaviours within a given course in week 2; "common-behaviour" indicates the most common behaviour in the same course in week 2; "non-rare behaviours" are any behaviours not in the bottom 25% (including but not limited to "common" behaviours); offline refers to students not engaging with the four activity-types in the LMS via the browser.

5. Discussion

As long as face-to-face teaching remains a major education mode in many universities, developing an understanding of student attendance behaviours is critical to maximizing the effectiveness and efficiency of physical and online teaching spaces. Through use of anonymous heat sensor data, distinct class attendance patterns are observable over time, and may be useful for instructors to assess their own class attendance at a glance, or as a starting point for course coordinators to compare classes within their course. Such class-level investigation is expected to help identify instructors who may need further assistance to improve their teaching practices, aimed at increasing student in-person participation and ultimately improving student outcomes. Course coordinators may also use this type of data when considering their room requirements for timetabling, potentially leading to additional improvements in space use efficiency. Further, for Property Services and Space Management departments, the data collected will support better planning and strategic decisions, and provide a more detailed understanding of the population profile identifying the university's future vertical transport, security, and facility management requirements.

As any instructor might expect, attendance patterns are also observed on a larger scale to depend on variables such as room capacity and class type. We observed in our initial study that the median occupancy in small and large teaching spaces decreased significantly over the semester. Almost all class types were often less than 50% attended throughout the semester; however, all demonstrated many instances of overfull classes, including tutorials with twice as many people in the room as it could hold. Such wide ranges of scaled occupancy indicate the difficulty of selecting a teaching space appropriate for a semester's worth of classes, as well as the need for a deeper understanding and modelling of student attendance behaviours.

Both physical and online attendance decrease through the course of the semester (RQ1: How does attendance, both in class and online, change over the duration of a semester?); the hypothesis that a decrease in physical attendance is compensated for by increased online activity is rejected. However, the fraction of students present online is, on average, considerably higher

ISSN 1929-7750 (online).

than the fraction present in lectures. The number of online behaviours displayed by students decreases with time, however behavioural evenness remains constant (RQ3: What is the distribution of behaviours?). These patterns suggest that those behaviours that are originally rare disappear from online activity throughout the semester, as evidenced by students shifting away from rare behaviours to more common ones later in the semester. These behavioural shifts within a course support the notion that students can show flexibility when engaging with online material in a course, but also that teaching innovation needs to account for different learners (Kloft, Stiehler, Zheng, & Pinkwart, 2014; Ramsden, 2003; Yuan & Powell, 2013).

Prior studies have shown that average attendance in modern university courses is poor (Hughes-Warrington, 2015; Stewart et al., 2011; Van Blerkom 1992; Traphagan et al., 2010; Cohn & Johnson, 2006). Consistent with other studies, our work shows that physical attendance drops over the duration of a semester, with the biggest drop in the first five weeks, and that this is a university-wide phenomenon in higher education courses at RMIT University (Hughes-Warrington, 2015; Stewart et al., 2011). The decrease in lecture attendance is not compensated for by an increase in online attendance, as the latter also decreases over the duration of the semester. However, this decrease is not monotonic, suggesting a different approach to online attendance by learners. In addition, there is no association between online behavioural distribution and physical attendance. These results suggest that making changes to the online course content in an attempt to lift physical attendance may not be effective.

Participation patterns are different in lectures and online, suggesting that the drivers behind each mode of engagement are different. Stewart et al. (2011) showed that the online activity within two courses appeared to be driven by assessment periods, since as assessments approached online participation increased. In our study, we do not observe sharp changes in participation within the semester because the 255 courses differ in their assessment deadlines; however, the strong decline by thousands of students reflects university-wide symptoms. For example, there was an increase in online participation from weeks 1 to 2, suggesting that the first elements of online material may be critical in maintaining engagement while students are finalizing their enrollments for the semester. However, closer examination of this short-term phenomenon is needed to test the hypothesis that poor accessibility to course material may first cause a greater initial engagement with the LMS quickly followed by disengagement from the course.

Identifying online behaviours and clustering students according to those behaviours has been a fruitful area of research in education, with examples at small and large scales (see e.g., Peckham & McCalla, 2012; and Kizilcec et al., 2013, respectively). Previously however, large-scale studies focusing on thousands of students within a MOOC usually centred on very few courses (e.g., Kizilcec et al., 2013; Tseng et al., 2016; Anderson et al., 2014), limiting the ability to generalize across a diversity of courses from different disciplines. In contrast, our university-wide approach defines a set of behaviours in a course-independent manner, capturing the distribution of behaviours in order to assess broad diversity patterns. Student behaviours can be categorized as common or rare (e.g., many or few students associated with particular behaviours). Yet, a rare behaviour in one course may be very common in another, particularly if there are significant differences in the way the course shells are structured. In this study we focus on changes in behavioural diversity over time for a given course; future work should examine differences in behavioural diversity between courses.

Many students change the way they participate online over the duration of a course reflected in the steady drop of behaviours over time (RQ2: Does student behaviour when engaging with online materials change over the duration of a semester?). In this study, the average number of behaviours exhibited within a course dropped from 19 to 16 over the duration of the semester, with 30.2% of students not engaging in any of the four online activities at week 11. Of the students who were engaging in rare behaviours initially, approximately half had shifted to more common behaviours by the end of the semester, 20% continued with rare behaviours, and approximately one-third did not engage in the activities online. In contrast, those students who were initially engaged in the most common behaviours tended to continue behaving in common ways, with less than 15% shifting to a rare behaviour later in the semester. This shift towards common behaviours is driven predominantly by "early rare behaviour" students, explaining both the drop in richness and the consistent evenness over time. Our study observed that some students disappeared by the end of the semester; however, of those who remained active online, many exhibited different behaviours in the final few weeks compared to how they acted initially. These behavioural shifts are consistent with other studies that demonstrated the plasticity of student behaviours (e.g., Kloft et al., 2014), and may be attributable to factors such as the identification of effective learning strategies within a course dependent on the course materials that are available, or that are particularly relevant to the discipline. However, evenness did not change throughout the semester, suggesting a combination of three factors: 1) some common behaviours lost students shifting to other less common behaviours, 2) students were not consistently active week to week, and 3) the students not participating within the LMS at week 11 came from all behavioural groups. This last factor reflects that a behaviour's level of rarity cannot predict future participation within the LMS.

It is important for course instructors to consider the behavioural distribution within their own course, and to interpret these patterns within their own context. This approach may help determine the underlying reasons that students engage in uncommon behaviours. Are students exploring? Do students have unusual preferences in accessing materials? Are they finding relevant materials outside of the course online space, such as the library? Importantly, are students unable to access content in common ways because of some form of disability? Or are they unmotivated students, interested only in doing the bare minimum online?

The broad generality in attendance and behavioural diversity showcased in this study allow individual instructors to compare their own courses to university-wide patterns. For example, a high-attendance — low-evenness pattern observed in a given course late in the semester may indicate a bias towards face-to-face engagement with course material, perhaps driven by an engaging lecturer. Alternatively, this behavioural pattern could reflect course content that is most valuably conveyed in person and having a course shell that directs students towards just a handful of ways to engage — perhaps used just as a place for students to download PDFs of lecture material. The opposite scenario, where a course sees relatively low attendance throughout semester, but has a high richness and evenness, is instead biased towards online transfer of knowledge; perhaps the lecturer is not an engaging speaker, but provides a diverse range of content materials, links extensively to external videos and other tools, and encourages discussions through the LMS course shell. (Of course, regardless of the physical and online participation patterns, the balance between face-to-face and online activities is a false dichotomy and not a zero-sum game where a drop in one mode requires an increase in the other. There are many important learning activities not captured at all in class attendance or the LMS, such as social media discussion groups, or recommended reading of academic texts.)

Learning design is significant in its influence on student engagement online (e.g., George-Walker & Keeffe, 2010; Ferguson et al., 2015; Rienties, Lewis, McFarlane, Nguyen, & Toetenel, 2018); for example, Rienties et al. (2018) found that 55% of variance in weekly online engagement was explained by the learning design of weekly activities in four language modules. Our work demonstrates that students tend to move towards common online behaviours, possibly as a result of the structure of the course shells. Further work in this space will examine how online student behaviours are influenced by the amount of content provided and how it is structured; however, individual instructors may already reflect on how their own pedagogy is encouraging or discouraging particular behaviours online and in the classroom.

The results described in this work provide a potential handle for instructors aiming to observe and understand the participation of their students, both online and in the lecture theatre. This can lead to reflection on the instructor's intended pedagogy, whether it is effective for their students, and assist in making changes to further enable students to improve their learning strategies. For example, those instructors trying to lift class attendance (and, hopefully, more active engagement) should focus on changes to their lecturing, as changing the online course shell will have minimum impact. It is important to ensure that students with uncommon approaches are being catered for, and not being actively discouraged by content structure. For example, if a student likes to learn from peer discussions, are online discussion boards being encouraged and maintained? Alternatively, is there time provided in lectures or tutorials for students to exchange ideas and learn from each other? Our goal here is not to advocate for all online tools to be fully utilized in the hope of maintaining the measured behaviour metrics, but to point out that the changes in behaviour metrics can be used to diagnose the reasons that students may disengage from a course. We also note that course-level participation measures resulting from this work are intended for use by instructors within their own context, and not for dictating what attendance patterns are most desirable, or asserting that students learn best when they exhibit specific behaviours.

Considerable research has provided strategies for lifting lecture attendance (e.g., Seary et al., 2014), such as scheduling multiple lectures for a given student on the same day (Kelly, 2012), or gamifying classes (O'Donovan, Gain, & Marais, 2013). Increasing attendance would generally ensure that instructors are imparting the course content to their students in a way they intend and can control; however, we note that many researchers have expressed their concern that a lecture is by no means the best way to teach all material (e.g., Freeman et al., 2014), nor does it necessarily suit all students (Kelly, 2012; Dolnicar et al., 2009). Online learning is here to stay, and tertiary institutions are slowly but surely moving away from using online course shells as simple lecture slide repositories (Nagel & Kotzé, 2010; Garrison, 2011; Wei & Chen, 2012). Instead, a blended online and face-to-face approach is desirable, as these methodologies can be more effective in combination than separately (Means et al., 2010; Bakia et al., 2014; Bernard et al., 2014).

This work confirms that students engage differently with online content over time than they do with face-to-face teaching. Stewart et al. (2011) encourages a greater diversity of online activities spread through a semester through blended learning to allow for consistent student participation. Myriad strategies and recommendations exist regarding how to design a truly engaging online course presence (e.g., Dixson, 2012; Guo, Kim, & Rubin, 2014; Vai & Sosulski, 2015; Revere & Kovach, 2011; McGee & Reis, 2012), such as utilizing a Community of Inquiry framework (Nagel & Kotzé, 2010). In particular, we support the suggestion of Salmon (2004) that we need to encourage social engagement within the course online space, particularly early on in the semester, as this is a clear alternative strategy to the dominant "content views" activity observed at RMIT.

6. Conclusion

This work describes an exploration of two ways that students can "attend" a course — through in-person attendance at lectures, and through online engagement with course content — by examining the average patterns of these attendance variables of hundreds of courses across a single semester. Attendance both online and in person decreases throughout the duration of a course, but with different patterns and rates over time. However, a higher proportion of students engage in some way with the online course shell than attend the lecture at all times during a course. This suggests that while the availability of online content does not necessarily impact student motivation to attend lectures, a significant fraction of students are only exposed to course content through online means.

We have also detailed a novel method to describe the ways in which a cohort of students are engaging with content online, by defining behaviours according to ranked counts of access to four different activity types. The richness tells us how many behaviours were exhibited within a cohort, providing insight into whether a course shell allows for different preferences for accessing course materials. The evenness tells us about the spread of students among those behaviours; a low evenness indicates a subset of dominant behaviours, while high evenness results when many behaviours are equally common. Now that baselines for these metrics are established at a university-wide level, instructors are able to compare the attendance patterns and distributions of behaviours within their own course, to examine how their students are participating in person and online relative to the average course. This would lead to further insight into what is driving these different patterns of participation, such as a captivating lecturer, or a well-structured course shell, and how these factors are able to maintain engagement levels over the period of a semester. We hope to provide instructors with a clearer sense of how they can provide content, both face-to-face and online, in order to ensure that as many students as possible are accessing this content in ways that the instructor intends.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors declared no financial support for the research, authorship, and/or publication of this article.

References

Amershi, S., & Conati, C. (2010). Automatic recognition of learner types in exploratory learning environments. In C. Romero, S. Ventura, M. Pechenizkiy, & R. S. J. d. Baker (Eds.), *Handbook of Educational Data Mining* (pp. 213–230). Boca Raton, FL: CRC Press. http://doi.org/10.1201/b10274-24

Anderson, A., Huttenlocher, D., Kleinberg, J., & Leskovec, J. (2014). Engaging with massive online courses. *Proceedings of the 23rd International Conference on World Wide Web* (WWW '14), 7–11 April 2014, Seoul, Republic of Korea (pp. 687–698). New York: ACM. http://doi.org/10.1145/2566486.2568042

Azab, E., Saksena, Y., Alghanem, T., Midle, J. B., Molgaard, K., Albright, S., & Karimbux, N. (2016). Relationship among dental students' class lecture attendance, use of online resources, and performance. *Journal of Dental Education*, *80*(4), 452–458.

Babb, K. A., & Ross, C. (2009). The timing of online lecture slide availability and its effect on attendance, participation, and exam performance. *Computers & Education*, *52*(4), 868–881. http://doi.org/10.1016/j.compedu.2008.12.009

Bakia, M., Means, B., & Murphy, R. (2014). *Learning online: What research tells us about whether, when and how*. London: Routledge.

Barker, L., Hovey, C. L., Subhlok, J., & Tuna, T. (2014). Student perceptions of indexed, searchable videos of faculty lectures. *Proceedings of the 2014 IEEE Frontiers in Education Conference* (FIE 2014), 22–25 October 2014, Madrid, Spain (pp. 1–8). IEEE Computer Society. http://doi.org/10.1109/FIE.2014.7044189

Bernard, R. M., Borokhovski, E., Schmid, R. F., Tamim, R. M., & Abrami, P. C. (2014). A meta-analysis of blended learning and technology use in higher education: From the general to the applied. *Journal of Computing in Higher Education*, *26*(1), 87–122. http://doi.org/10.1007/s12528-013-9077-3

Brennan, A., Peace, C., & Munguia, P. (2018). Classroom size, activity and attendance: Scaling up drivers of learning space occupation. *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (LAK '18), 5–9 March 2018, Sydney, NSW, Australia (pp. 255–259). New York: ACM. http://doi.org/10.1145/3170358.3170401

Cohn, E., & Johnson, E. (2006). Class attendance and performance in principles of economics. *Education Economics*, *14*(2), 211–233. http://doi.org/10.1080/09645290600622954

Dixson, M. D. (2012). Creating effective student engagement in online courses: What do students find engaging? *Journal of* *the Scholarship of Teaching and Learning*, *10*(2), 1–13.

Dolnicar, S., Kaiser, S., Matus, K., & Vialle, W. (2009). Can Australian universities take measures to increase the lecture attendance of marketing students? *Journal of Marketing Education*, *31*(3), 203–211. http://doi.org/10.1177/0273475309345202

Dutt, A., Aghabozrgi, S., Ismail, M. A. B., & Mahroeian, H. (2015). Clustering algorithms applied in educational data mining. *International Journal of Information and Electronics Engineering, 5*(2), 112. http://doi.org/10.7763/IJIEE.2015.V5.513

Ferguson, R., Clow, D., Beale, R., Cooper, A. J., Morris, N., Bayne, S., & Woodgate, A. (2015). Moving through MOOCs: Pedagogy, learning design and patterns of engagement. In G. Conole, T. Klobučar, C. Rensing, J. Konert, E. Lavoué (Eds.), *Design for Teaching and Learning in a Networked World. Lecture Notes in Computer Science*, vol. 9307 (pp. 70–84). Springer, Cham. http://doi.org/10.1007/978-3-319-24258-3_6

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences, 111*(23), 8410–8415. http://doi.org/10.1073/pnas.1319030111

Garrison, D. R. (2011). *E-learning in the 21st century: A framework for research and practice*. Abingdon, UK: Taylor & Francis.

George-Walker, L. D., & Keeffe, M. (2010). Self-determined blended learning: A case study of blended learning design. *Higher Education Research & Development, 29*(1), 1–13. http://doi.org/10.1080/07294360903277380

Grabe, M. (2005). Voluntary use of online lecture notes: Correlates of note use and note use as an alternative to class attendance. *Computers & Education, 44*(4), 409–421. http://doi.org/10.1016/j.compedu.2004.04.005

Grabe, M., & Christopherson, K. (2005). Evaluating the advantages and disadvantages of providing lecture notes: The role of internet technology as a delivery system and research tool. *The Internet and Higher Education, 8*(4), 291–298. http://doi.org/10.1016/j.iheduc.2005.09.002

Grabe, M., Christopherson, K., & Douglas, J. (2005). Providing introductory psychology students access to online lecture notes: The relationship of note use to performance and class attendance. *Journal of Educational Technology Systems*, *33*(3), 295–308. http://doi.org/10.2190/G5RF-DMWG-WV1G-TMGG

Gump, S. E. (2006). Guess who's (not) coming to class: Student attitudes as indicators of attendance. *Educational Studies, 32*(1), 39–46. http://doi.org/10.1080/03055690500415936

Guo, P. J., Kim, J., & Rubin, R. (2014). How video production affects student engagement: An empirical study of MOOC videos. *Proceedings of the 1st ACM Conference on Learning @ Scale* (L@S 2014), 4–5 March 2014, Atlanta, Georgia, USA (pp. 41–50). New York: ACM. http://doi.org/10.1145/2556325.2566239

Hughes-Warrington, M. (2015, July 6). That sinking feeling: Counting the cost of live lectures. Tumblr post. https://missunitwocents.tumblr.com/post/123364615920/that-sinking-feeling-counting-the-cost-of-live

Kelly, G. E. (2012). Lecture attendance rates at university and related factors. *Journal of Further and Higher Education, 36*(1), 17–40. http://doi.org/10.1080/0309877X.2011.596196

Kinash, S., Knight, D., & McLean, M. (2015). Does digital scholarship through online lectures affect student learning? *Journal of Educational Technology & Society*, *18*(2), 129–139.

Kizilcec, R. F., Piech, C., & Schneider, E. (2013). Deconstructing disengagement: Analyzing learner subpopulations in massive open online courses. *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge* (LAK '13), 8–12 April 2013, Leuven, Belgium (pp. 170–179). New York: ACM. http://doi.org/10.1145/2460296.2460330

Khong, R. W., Dunn, J. S., Lim, C. M., & Yap, W. S. (2016). Why do students attend lectures? Exploring justifications for attendance among undergraduate students from a British university in Asia. *The Journal of Developing Areas, 50*(5), 497–506. http://doi.org/10.1353/jda.2016.0059

Kloft, M., Stiehler, F., Zheng, Z., & Pinkwart, N. (2014). Predicting MOOC dropout over weeks using machine learning methods. *Proceedings of the Workshop on Modeling Large Scale Social Interaction in MOOCs at the 2014 Conference on Empirical Methods in Natural Language Processing* (EMNLP 2014), 25 October 2014, Doha, Qatar (pp. 60–65). Association for Computational Linguistics.

Magurran, A. E. (1988). Why diversity? *Ecological diversity and its measurement* (pp. 1–5). Springer, Dordrecht. http://doi.org/10.1007/978-94-015-7358-0_1

McGee, P., & Reis, A. (2012). Blended course design: A synthesis of best practices. *Journal of Asynchronous Learning Networks*, *16*(4), 7–22.

Means, B., Toyama, Y., Murphy, R., Bakia, M., & Jones, K. (2010, September). *Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies*. U.S. Department of Education, Office of

Planning, Evaluation, and Policy Development. https://www2.ed.gov/rschstat/eval/tech/evidence-based-practices/finalreport.pdf

Mukala, P., Buijs, J. C. A. M., & Van Der Aalst, W. M. P. (2015). Exploring students' learning behaviour in MOOCs using process mining techniques. BPM reports, Vol. 1510. Department of Mathematics and Computer Science, University of Technology, Eindhoven, The Netherlands. https://research.tue.nl/en/publications/exploring-students-learning-behaviour-in-moocs-using-process-mini

Nagel, L., & Kotzé, T. G. (2010). Supersizing e-learning: What a CoI survey reveals about teaching presence in a large online class. *The Internet and Higher Education, 13*(1–2), 45–51. http://doi.org/10.1016/j.iheduc.2009.12.001

O'Donovan, S., Gain, J., & Marais, P. (2013). A case study in the gamification of a university-level games development course. *Proceedings of the South African Institute for Computer Scientists and Information Technologists Conference* (SAICSIT '13), 7–9 October 2013, East London, South Africa (pp. 242–251) New York: ACM. http://doi.org/10.1145/2513456.2513469

Peckham, T., & McCalla, G. (2012). Mining student behavior patterns in reading comprehension tasks. In K. Yacef, O. Zaiane, A. Hershkovitz, M. Yudelson, & J. Stamper (Eds.), *Proceedings of the 5th International Conference on Educational Data Mining* (EDM2012), 19–21 June 2012, Chania, Greece (pp. 87–94). International Educational Data Mining Society. http://educationaldatamining.org/EDM2012/uploads/procs/EDM_2012_proceedings.pdf

Ramsden, P. (2003). *Learning to teach in higher education*. London: Routledge.

Revere, L., & Kovach, J. V. (2011). Online technologies for engaged learning: A meaningful synthesis for educators. *Quarterly Review of Distance Education*, *12*(2), 113–124. http://doi.org/10.1080/15236803.2018.1429817

Rienties, B., Lewis, T., McFarlane, R., Nguyen, Q., & Toetenel, L. (2018). Analytics in online and offline language learning environments: The role of learning design to understand student online engagement. *Computer Assisted Language Learning, 31*(3), 273–293. http://doi.org/10.1080/09588221.2017.1401548

Salmon, G. (2004). *E-moderating: The key to teaching and learning online*. London: Psychology Press.

Seary, K., James, T., & Conradie, H. (2014). Designing practical strategies to increase STEPS students' attendance at face-to-face, on campus classes: Preliminary findings. Paper presented to the FABENZ: Challenges and Innovation Conference, 4–5 December 2014, Tauranga, New Zealand. https://www.academia.edu/19639837/Designing_practical_strategies_to_increase_STEPS_students_attendance_at_face-to-face_on_campus_classes_Preliminary_findings

Stewart, M., Stott, T., & Nuttall, A. M. (2011). Student engagement patterns over the duration of level 1 and level 3 geography modules: Influences on student attendance, performance and use of online resources. *Journal of Geography in Higher Education, 35*(1), 47–65. http://doi.org/10.1080/03098265.2010.498880

Traphagan, T., Kucsera, J. V., & Kishi, K. (2010). Impact of class lecture webcasting on attendance and learning. *Educational Technology Research and Development*, *58*(1), 19–37. http://doi.org/10.1007/s11423-009-9128-7

Tseng, S. F., Tsao, Y. W., Yu, L. C., Chan, C. L., & Lai, K. R. (2016). Who will pass? Analyzing learner behaviors in MOOCs. *Research and Practice in Technology Enhanced Learning, 11*(8). http://doi.org/10.1186/s41039-016-0033-5

Vai, M., & Sosulski, K. (2015). *Essentials of online course design: A standards-based guide*. London: Routledge.

Van Blerkom, M. L. (1992). Class attendance in undergraduate courses. *The Journal of Psychology, 126*(5), 487–494. http://doi.org/10.1080/00223980.1992.10543382

Weatherley, J. N., Grabe, M., & Arthur, E. I. (2003). Providing introductory psychology students access to lecture slides via Blackboard 5: A negative impact on performance. *Journal of Educational Technology Systems*, *31*, 463–474. http://doi.org/10.2190/KRW7-QHFY-AY3M-FFJC

Wei, C. W., & Chen, N. S. (2012). A model for social presence in online classrooms. *Educational Technology Research and Development, 60*(3), 529–545. http://doi.org/10.1007/s11423-012-9234-9

Worthington, D. L., & Levasseur, D. G. (2015). To provide or not to provide course PowerPoint slides? The impact of instructor-provided slides upon student attendance and performance. *Computers & Education, 85*, 14–22. http://doi.org/10.1016/j.compedu.2015.02.002

Yuan, L., & Powell, S. (2013). MOOCs and disruptive innovation: Implications for higher education. *eLearning Papers, In-depth*, *33*(2), 1–7.

Appendix

A summary of the online and physical activity of each included course is provided (Table 3). The course shell size indicates the number of students enrolled in the course LMS. Certain courses captured attendance data for more than one lecture stream, and so the average number of students enrolled in the captured streams is recorded. The percentage of active students each week (both online and attending lectures) is averaged over the twelve weeks of the semester. The richness (ranging from 1 to 64) and evenness (bounded by 0 and 1) are also averaged over the semester.

In the case of large courses, the recorded lecture class may be a subset of the online course shell, as the students are split among multiple lecture streams, not all of which are captured in our dataset. In other cases, multiple courses may share a single lecture stream, and so enrollments in the shared lecture are higher than those in the specific course shell.

The physical attendance data of five courses (with IDs 5, 163, 233, 240, and 255) was not included, as these courses did not meet the requirements of exactly 12 weeks of attendance data for an associated lecture stream, and no more than one week with zero attendance.

Table 3: The Physical and Online Engagement of 255 Courses. Note: Courses are ranked by proportion of active students in the course; size = number of students. Five courses do not have physical attendance data recorded here, as they did not meet the final requirements for inclusion.

Course ID	Online								Physical		
	Course shell size	Avg. active students (%)	Average pc each week of enrolled students who: viewed content (%)	downloaded content (%)	viewed discussions (%)	accessed external apps (%)	Avg. richness	Avg. evenness	Num. lecture streams	Avg. lecture size	Avg. lecture att. (%)
1	75	94.8	91.5	87.6	46.1	30.1	15	0.81	1	72	60.2
2	22	94.1	91.4	80.9	42.3	56.4	9.9	0.9	2	127.5	15.8
3	98	93.8	89.7	85.1	58.6	31.8	23.4	0.82	1	98	29.4
4	30	93.3	73.3	83.3	42.0	3.3	9.8	0.86	2	29.5	41
5	48	92.3	88.3	87.3	35.0	51.7	15.5	0.87			
6	32	92.2	87.8	86.9	33.8	19.4	10.1	0.84	1	32	40.6
7	24	92.1	60.8	78.8	44.2	42.5	14.7	0.94	1	31	71
8	104	91.6	77.2	86.5	46.6	43.3	27.2	0.87	2	102	40.3
9	49	91.6	87.3	80.0	39.4	0.6	8.6	0.76	2	49	57.2
10	25	90.4	81.2	75.6	47.6	20.0	11.2	0.88	1	25	72.7
11	56	90.2	87.0	80.5	46.3	52.1	18.5	0.89	1	54	19.9
12	34	89.7	85.0	70.6	60.3	63.5	14.7	0.91	1	126	42.1
13	81	89.4	81.2	78.6	60.2	32.1	22.2	0.86	2	76.5	50.7
14	56	89.3	85.4	85.0	27.3	21.3	11.9	0.78	1	55	48.3
15	28	89.3	37.5	82.5	31.1	24.6	11.6	0.86	1	28	53.6
16	27	88.9	78.5	82.2	13.0	29.3	9.5	0.82	1	27	71.9
17	177	88.8	85.5	74.5	42.8	41.5	19.7	0.77	1	172	23.9
18	101	88.7	77.7	83.2	33.6	20.1	20.1	0.81	1	93	35.3
19	119	88.6	66.2	78.9	41.3	49.7	32.8	0.89	2	108	37.9
20	141	88.2	83.7	77.4	26.5	31.1	23.1	0.76	2	185	26.4
21	93	88.2	86.7	74.5	22.4	35.3	12.3	0.7	2	90.5	18.7
22	182	88.1	66.0	76.3	49.4	37.9	39.5	0.87	4	181	26.1
23	110	87.9	81.4	49.5	60.7	12.6	21.3	0.84	1	80	48.8
24	25	87.6	77.6	74.8	34.4	24.0	11.3	0.88	1	25	78.7
25	117	86.6	75.8	77.9	38.4	31.0	25.6	0.84	2	117	32.8

ISSN 1929-7750 (online).

26	254	86.5	73.3	77.0	40.7	41.7	40.1	0.86	1	245	22.3
27	67	86.4	83.4	77.2	37.2	38.5	19.1	0.86	2	65.5	21.3
28	76	86.4	78.7	72.4	34.2	56.2	21.3	0.86	1	73	24.3
29	132	86.3	80.3	79.1	52.6	29.5	24.7	0.86	2	132	37.2
30	232	86.3	82.1	78.0	42.3	35.5	30.7	0.79	2	226	29.7
31	84	86.1	81.3	73.1	31.4	47.1	20	0.84	1	84	34
32	230	85.9	62.8	83.3	16.4	18.7	20.9	0.65	3	147.3	22.2
33	16	85.6	68.8	42.5	18.1	80.6	7.8	0.89	1	15	94.4
34	140	85.6	49.5	64.5	69.1	5.5	19.3	0.83	2	139.5	57.1
35	47	85.5	63.4	81.7	2.8	31.5	10.3	0.85	2	42	54.7
36	202	85.5	74.9	74.0	16.0	11.3	19.2	0.7	1	62	25
37	132	85.5	83.5	36.4	33.8	3.7	10.6	0.71	1	127	35.4
38	533	85.3	77.9	73.0	31.0	35.6	44.1	0.77	1	214	26.8
39	65	85.2	67.7	82.2	18.9	11.5	11.7	0.78	1	64	68.1
40	84	85.2	76.5	76.3	33.0	22.4	19.3	0.81	2	80.5	44.1
41	71	85.2	84.4	75.8	11.0	74.1	13.4	0.86	1	68	26.2
42	505	85	62.2	1.8	21.3	82.4	17.2	0.64	1	157	34.9
43	72	84.9	80.3	79.3	25.0	26.5	15.4	0.81	2	72	36.8
44	63	84.9	57.1	80.2	37.6	7.1	13.5	0.84	1	61	43.9
45	245	84.9	81.7	75.9	18.0	19.9	23.3	0.67	1	243	31.1
46	50	84.8	59.8	60.4	50.6	34.0	21.8	0.93	1	47	69.4
47	32	84.7	81.3	79.7	11.9	50.3	8.7	0.8	1	21	154
48	110	84.6	80.3	74.8	6.7	64.6	14.5	0.77	2	109.5	19.1
49	270	84.5	77.9	73.4	25.9	29.9	29.8	0.75	1	270	41.9
50	255	84.5	77.8	59.1	53.8	29.5	35.1	0.83	1	251	35.9
51	40	84.3	73.3	77.3	23.8	22.0	11.7	0.85	1	38	54.8
52	124	84.3	76.9	65.4	17.2	55.6	20.4	0.78	1	119	35.1
53	87	84.1	67.2	76.9	34.3	12.6	17.5	0.79	2	83.5	52.9
54	33	83.9	68.5	60.9	37.6	19.7	14.1	0.9	1	33	101.7
55	21	83.3	75.2	70.5	53.3	1.4	8	0.9	1	17	135.8
56	71	83	69.3	65.4	47.9	46.5	25.7	0.92	1	67	27.2
57	133	82.8	80.5	58.8	38.1	11.5	15.1	0.76	1	130	37.8
58	204	82.8	76.7	74.6	7.4	44.3	22.1	0.79	1	200	55
59	70	82.7	78.7	59.6	33.1	34.0	13.8	0.82	1	70	25.2
60	71	82.5	71.3	69.9	54.2	73.5	19.2	0.85	1	69	54.3
61	40	82.5	73.5	76.3	20.5	8.0	8.7	0.83	1	39	67.1
62	22	82.3	81.4	67.3	18.2	9.5	6.2	0.78	1	22	96.2
63	291	82	75.7	74.7	29.8	18.8	34.3	0.74	1	260	36.9
64	15	82	71.3	67.3	22.0	0.0	5.9	0.9	1	36	75
65	64	81.9	49.4	72.2	53.6	10.2	15.8	0.88	1	63	70.2
66	58	81.9	48.3	65.9	44.1	32.1	23.3	0.92	2	55.5	32.3
67	132	81.8	54.2	69.2	26.0	21.8	26.3	0.82	1	130	41.7
68	50	81.6	77.4	76.6	15.0	22.6	10.6	0.8	1	46	41.5
69	88	81.4	71.7	71.5	39.8	19.3	21.7	0.85	3	85	37
70	54	81.1	71.9	75.2	29.1	19.8	14.8	0.85	1	51	34.6
71	10	81	77.0	73.0	35.0	17.0	5.5	0.95	1	44	56.8

ISSN 1929-7750 (online). The Journal of Learning Analytics works under a Creative Commons License, Attribution - NonCommercial-NoDerivs 3.0 Unported (CC BY-NC-ND 3.0)

72	246	81	74.1	66.2	40.9	15.0	28.9	0.81	1	240	52.5
73	51	80.8	69.0	69.4	37.8	19.2	14.9	0.88	2	49	103.5
74	107	80.7	47.3	56.8	73.4	27.9	28.6	0.86	1	100	13.3
75	340	80.5	68.1	63.9	38.9	48.1	45.9	0.86	2	295	18.5
76	69	80.3	68.1	75.4	44.5	1.2	9.7	0.79	1	68	26.5
77	77	80.3	76.2	36.0	27.3	12.2	14.3	0.77	1	76	64.9
78	36	80.3	68.9	65.6	30.3	20.8	13.1	0.89	1	36	51.8
79	53	80	67.0	55.1	28.3	57.7	16.9	0.85	1	53	53.3
80	45	80	68.0	67.6	20.4	8.2	9.7	0.8	1	45	48.5
81	108	80	69.5	69.3	36.1	32.1	27	0.87	1	108	24.3
82	128	79.9	54.8	25.8	17.6	77.3	18.5	0.73	1	127	61.6
83	58	79.8	68.6	71.2	30.9	11.0	11.7	0.83	1	58	71.5
84	38	79.7	56.1	70.3	47.6	5.5	11.5	0.9	1	37	62.4
85	636	79.6	69.7	63.0	31.7	57.0	49.8	0.82	1	258	30.4
86	320	79.4	72.0	68.1	15.0	38.6	33.5	0.75	3	292.7	11
87	78	79	72.8	68.1	15.6	52.6	18.4	0.85	1	67	43.7
88	53	78.9	76.2	70.4	18.5	11.9	11.4	0.78	1	46	89.5
89	500	78.9	64.5	56.1	36.0	26.2	42	0.82	1	133	41
90	106	78.8	56.5	49.4	46.5	29.7	25	0.87	1	105	47.3
91	138	78.8	70.7	64.7	30.1	18.6	21.4	0.79	1	136	47.8
92	34	78.8	70.3	74.1	8.2	41.5	9.3	0.87	2	32.5	58.3
93	79	78.5	66.7	59.2	28.4	46.1	20.9	0.87	1	78	49.7
94	22	78.2	71.8	72.7	3.6	2.7	4	0.76	1	22	65.5
95	50	78.2	64.4	65.2	35.6	9.8	13	0.83	1	44	90.2
96	80	78.1	65.0	65.0	43.3	27.4	23.5	0.89	1	80	31
97	41	78	72.7	63.7	20.0	12.7	10.2	0.82	1	41	19.1
98	91	77.7	61.0	66.5	22.4	22.9	19.5	0.81	1	89	46.7
99	87	77.7	74.1	51.7	29.3	19.2	13.3	0.8	1	87	45.3
100	35	77.7	48.0	50.0	70.3	13.7	11.9	0.9	1	32	22.4
101	476	77.2	65.0	52.1	42.0	14.6	37	0.79	1	139	45.9
102	118	77.1	48.9	31.3	69.6	22.0	23.3	0.8	1	58	21.3
103	194	76.7	71.2	67.7	28.3	19.2	23.7	0.75	1	175	38.8
104	60	76.7	65.5	57.2	33.8	0.0	10.5	0.83	1	59	62.1
105	15	76.7	73.3	61.3	38.7	14.0	5.6	0.9	1	12	47.9
106	229	76.6	54.1	67.5	11.3	24.3	23.8	0.75	2	215.5	21.3
107	143	76.5	62.2	50.6	45.8	12.1	23.9	0.86	1	132	42.6
108	1389	76.5	66.7	63.5	28.0	13.0	46.3	0.68	2	103.5	38.8
109	190	76.2	70.8	60.3	21.9	32.0	24.8	0.78	1	177	40.3
110	208	76.2	56.1	60.9	26.4	29.0	29.4	0.84	1	205	45.8
111	78	75.8	63.8	62.7	10.9	18.2	15	0.8	2	74	53.4
112	98	75.8	71.1	69.1	14.6	30.8	16.5	0.75	1	98	49.9
113	1292	75.7	65.3	68.0	31.5	21.7	50.7	0.73	1	234	33.7
114	32	75.6	52.2	55.6	47.5	5.6	9.3	0.88	1	32	37.2
115	171	75.4	68.3	64.2	26.6	3.4	16.8	0.77	1	168	42.7
116	19	75.3	56.8	63.7	9.5	11.6	6.3	0.9	1	19	71.1
117	39	75.1	41.0	38.5	71.0	17.4	13.4	0.82	1	36	16.9

118	57	74.9	66.1	36.0	24.6	28.1	15.7	0.85	1	56	39.3
119	121	74.6	41.3	44.1	69.6	26.4	27.4	0.81	1	60	18.8
120	215	74.3	67.9	62.0	23.7	16.8	23.9	0.73	1	172	27.9
121	168	73.9	63.1	58.2	5.5	40.5	19.8	0.82	1	157	47.9
122	31	73.9	57.1	58.4	42.9	16.8	11.1	0.92	1	30	49.2
123	128	73.9	69.0	67.1	10.2	13.8	14.3	0.71	2	125.5	35.8
124	50	73.8	67.0	58.0	35.0	16.8	12.8	0.85	1	115	51.7
125	88	73.8	63.1	6.8	12.4	28.8	12.5	0.68	1	87	18.8
126	68	73.7	57.8	41.3	44.3	35.6	23	0.92	1	67	25
127	76	73.3	67.4	52.0	26.8	21.8	16.2	0.83	1	67	54.6
128	67	73.3	57.8	15.4	46.1	13.0	13.6	0.78	1	64	62.6
129	109	73.2	63.9	62.9	18.3	35.3	19.2	0.79	1	104	27.7
130	41	73.2	41.2	47.3	54.4	8.0	11.7	0.85	1	40	77.9
131	44	73.2	52.5	63.9	27.5	8.2	10.8	0.86	1	40	94
132	62	73.1	35.8	61.8	24.8	17.7	16.4	0.83	1	57	47.1
133	57	73	61.2	51.6	45.6	30.2	18.6	0.9	1	52	36.4
134	366	72.8	63.5	65.5	28.2	11.1	28.2	0.72	1	254	62.3
135	1500	72.7	55.8	61.2	27.3	36.0	49.4	0.74	1	236	24.1
136	106	72.7	70.2	56.6	17.0	10.1	14.5	0.73	1	105	41.6
137	78	72.6	70.0	65.5	10.0	11.0	9.1	0.67	1	78	45.1
138	12	72.5	71.7	54.2	3.3	3.3	3.4	0.84	1	12	97
139	129	72.3	58.0	52.8	40.9	12.9	22.4	0.84	1	128	50.7
140	84	72.3	54.3	62.0	36.4	23.8	21.3	0.89	1	84	30.4
141	28	72.1	66.4	64.3	21.1	1.1	6.3	0.82	1	28	41.6
142	78	72.1	58.1	57.1	31.3	33.5	23.5	0.89	1	70	26.7
143	102	72	61.1	60.7	37.8	16.5	21.7	0.83	1	99	64.9
144	25	72	64.0	64.0	34.8	14.0	9.3	0.89	1	25	52.7
145	74	72	69.2	52.4	23.2	38.2	14.3	0.83	1	58	57.5
146	12	71.7	45.8	50.0	26.7	35.8	5.4	0.92	1	12	88.9
147	699	71.7	55.9	58.2	41.6	12.0	38.2	0.75	1	107	23.1
148	141	71.6	65.1	49.6	34.1	13.5	20.2	0.78	1	137	33.4
149	189	71.6	57.5	60.8	30.5	13.3	26.6	0.82	1	182	31.7
150	127	71.3	65.7	62.2	11.3	41.3	18	0.77	3	126.3	28.2
151	30	71	58.7	58.3	24.3	17.7	10.9	0.89	1	29	61.8
152	25	70.8	62.4	67.6	4.8	0.0	3.9	0.81	1	22	92.1
153	511	70.8	65.6	60.0	28.5	16.7	30.3	0.68	1	173	57.4
154	55	70.7	55.6	52.9	24.5	54.5	15.4	0.89	1	51	59.8
155	348	70.5	64.0	54.4	12.7	43.9	30.8	0.82	1	344	19.7
156	117	70.5	58.1	51.1	31.3	7.0	17.5	0.85	1	60	80.4
157	56	70.5	60.2	59.1	24.1	25.5	14.5	0.88	2	103	33
158	33	70.3	55.2	59.1	26.1	8.5	9.8	0.86	1	32	63.8
159	68	70.1	63.5	62.6	29.4	4.0	11.6	0.81	1	68	86.4
160	123	70.1	59.8	58.5	15.4	12.5	17.8	0.76	1	123	16.8
161	14	70	55.0	59.3	28.6	19.3	6.6	0.94	1	12	74.3
162	22	70	55.9	53.2	9.1	37.3	8.3	0.94	1	62	49.1
163	20	70	58.0	60.0	35.5	10.0	8.3	0.85			

164	77	69.9	57.0	53.2	29.1	33.6	20.4	0.88	1	69	17.3
165	82	69.6	66.5	48.2	18.8	12.6	13.5	0.79	1	82	43.5
166	174	69.5	63.0	34.8	31.2	41.3	31.1	0.88	1	131	19.1
167	19	69.5	56.3	56.3	28.4	10.5	7.6	0.89	1	19	42.5
168	40	69.5	55.8	54.3	34.5	20.8	13.3	0.88	1	35	33.6
169	193	69.1	49.7	49.4	31.2	20.5	29.5	0.84	1	184	30.6
170	368	68.8	55.2	50.3	28.8	18.8	35.3	0.8	1	113	39.9
171	311	68.7	61.7	57.4	18.7	23.1	28.2	0.76	1	311	29.8
172	54	68.5	54.8	51.9	37.0	15.7	15.5	0.9	1	54	74.7
173	81	68.4	48.5	49.9	34.3	31.7	22.1	0.9	2	76	31
174	18	68.3	53.3	56.7	31.1	7.8	6.5	0.91	1	18	90.4
175	165	68.1	53.6	40.5	27.8	28.9	27.6	0.85	1	159	42.5
176	217	67.8	60.9	53.8	26.2	33.3	31.6	0.83	1	142	45.5
177	453	67.6	65.3	55.4	9.6	2.3	15.3	0.56	1	145	50.4
178	103	67.5	57.1	57.3	12.8	8.5	13.7	0.74	1	102	39.2
179	450	67.1	54.4	31.7	31.2	18.9	36.5	0.79	1	211	41.7
180	46	67	58.7	52.4	7.2	19.8	10.5	0.84	1	83	46.9
181	194	66.9	59.9	59.6	23.2	0.0	10.9	0.7	2	193.5	43.5
182	108	66.9	57.7	61.4	11.9	10.6	13.1	0.73	1	107	47.1
183	59	66.8	45.6	54.1	39.5	15.8	16.4	0.89	1	55	46.2
184	57	66.8	60.9	55.1	14.9	3.5	8.2	0.73	1	55	43.6
185	103	66.7	61.9	45.6	23.9	16.6	18.4	0.8	1	103	59
186	18	66.7	42.2	47.2	41.7	23.9	8.7	0.93	1	18	69.9
187	240	66.5	61.2	51.3	15.9	25.5	21.7	0.76	1	207	26.9
188	34	66.2	57.1	50.3	28.5	9.1	9.6	0.87	1	31	83.6
189	53	66	47.0	28.1	26.0	38.7	12.4	0.87	1	53	57.3
190	194	66	42.6	54.5	40.5	16.9	28.4	0.85	1	152	47.3
191	69	65.9	55.1	53.3	32.6	0.1	11.4	0.84	1	69	57.8
192	22	65.9	44.5	55.0	40.5	13.2	9.5	0.95	1	22	78.4
193	70	65.7	60.9	41.3	24.3	23.4	14.1	0.83	1	69	62.6
194	104	65.5	47.7	56.7	21.4	3.6	13.4	0.82	1	103	32.6
195	393	65.3	55.3	55.6	18.9	7.4	26.7	0.72	2	116	37.8
196	38	65.3	56.6	53.7	33.2	16.8	11.4	0.9	1	38	57.7
197	153	65.1	54.1	52.7	21.0	10.3	18.6	0.78	1	152	27.3
198	79	64.9	54.9	55.3	18.1	0.1	8.9	0.8	1	77	35.8
199	104	64.8	50.5	23.8	36.0	18.7	20.1	0.85	1	104	30.9
200	83	64.8	56.3	38.4	29.9	20.4	18.5	0.87	1	81	27.2
201	1292	64.6	49.2	53.2	13.5	2.3	21.1	0.71	1	165	37.8
202	130	64.5	52.5	47.4	36.4	30.5	26.8	0.86	1	126	41.8
203	225	64.2	49.0	48.5	17.4	25.5	27.3	0.81	1	225	20.8
204	123	64.2	57.3	52.8	19.1	10.2	16.6	0.78	1	40	15.7
205	15	64	55.3	36.7	36.7	5.3	5.6	0.93	1	14	108.4
206	12	63.3	55.8	53.3	3.3	0.0	2.9	0.63	1	12	103.5
207	66	62.9	46.7	46.7	30.2	17.4	16.6	0.89	1	62	41.4
208	45	62.2	43.1	48.7	17.8	2.4	8.4	0.85	1	39	47.6
209	285	62	56.6	54.0	15.6	10.4	21.6	0.68	1	141	34.4

210	100	61.8	48.1	49.8	31.6	4.1	13.8	0.83	1	122	45.6
211	75	61.7	57.3	50.0	5.3	13.2	10.7	0.77	1	75	29.7
212	124	61.5	50.2	51.4	29.3	5.3	17.8	0.83	1	120	47
213	98	61.4	25.8	1.9	47.0	18.9	11.2	0.72	1	154	39.4
214	38	61.3	49.2	47.6	17.6	10.5	9.6	0.87	1	38	78.9
215	339	61	46.7	48.0	20.8	3.5	21.1	0.75	1	91	24.5
216	40	60.8	49.5	47.5	12.0	10.0	9.7	0.85	1	40	54.3
217	150	60.7	51.3	45.7	28.5	6.2	16.8	0.8	1	147	41.4
218	38	60.5	56.8	29.5	15.5	0.0	5.9	0.86	2	34	57.8
219	73	60	47.7	12.6	37.4	6.4	9.8	0.84	1	72	13.7
220	231	59.7	35.8	49.6	29.3	14.3	28.7	0.82	1	194	11.3
221	25	59.6	38.0	47.2	16.4	0.8	6.3	0.87	1	25	53.7
222	67	59	50.9	49.1	12.2	16.1	12.8	0.84	1	76	126.6
223	477	58.4	53.8	50.5	12.4	2.3	15.7	0.65	1	142	28.1
224	149	58.1	42.0	32.2	27.0	12.6	18.1	0.79	1	147	63.5
225	53	57.9	30.6	52.8	4.5	0.0	5.8	0.79	2	51.5	79.8
226	288	57.7	53.2	42.8	11.9	9.3	20.9	0.67	1	121	28.4
227	48	56.9	52.3	47.7	16.5	6.7	8.9	0.82	1	41	50.8
228	16	56.9	40.6	35.0	36.3	15.6	6	0.92	1	20	32.3
229	19	56.8	45.3	40.5	22.6	2.1	6	0.93	1	19	41.7
230	104	56.7	47.3	43.3	10.3	16.2	15.6	0.74	1	133	18.7
231	68	56.3	46.6	52.1	7.5	4.4	8.3	0.78	1	68	54.7
232	16	56.3	53.8	43.1	16.9	2.5	4.6	0.89	1	16	65.6
233	47	56	47.4	21.1	22.8	3.6	7.4	0.81			
234	178	55.7	31.7	43.9	21.1	7.2	18.6	0.79	1	145	37.6
235	61	55.7	47.2	13.8	23.6	10.5	9.7	0.73	1	61	45.8
236	121	54	33.0	43.1	17.2	5.5	14	0.81	1	115	25.9
237	209	53.3	45.2	24.1	14.6	42.6	21.6	0.84	1	202	14.8
238	83	53	34.7	41.6	22.7	4.0	14	0.85	1	98	80.6
239	18	52.8	46.7	50.6	3.3	0.0	2.8	0.84	1	18	68.5
240	75	52.8	38.3	44.4	18.0	8.1	13	0.84			
241	120	52.5	48.9	26.1	12.7	28.7	14.6	0.82	1	120	51
242	49	52.2	35.5	26.5	29.6	5.3	9.3	0.82	1	49	23.6
243	38	51.8	41.1	43.7	8.9	0.0	5.1	0.78	1	37	77.6
244	58	51.7	10.2	1.4	41.9	17.2	7.2	0.72	1	55	43.3
245	19	51.6	33.2	26.3	26.3	22.6	7.2	0.94	2	17.5	72.8
246	171	50.2	25.7	10.6	36.9	16.1	17.8	0.69	1	171	54.9
247	89	49.8	38.4	32.6	20.0	5.7	13.9	0.86	1	89	17.9
248	15	49.3	31.3	32.0	14.0	5.3	4.7	0.89	1	11	95
249	15	46.7	44.7	13.3	6.0	4.7	3.3	0.86	1	15	68.5
250	130	45.4	29.5	14.2	11.2	14.5	13.8	0.74	1	128	37.2
251	46	42.6	38.9	30.7	9.3	7.6	8.1	0.89	1	46	67.9
252	45	40.2	36.0	21.1	15.3	0.0	5	0.84	1	43	45.7
253	134	37.4	34.3	26.4	2.6	10.8	10.1	0.79	1	130	55
254	17	18.8	5.9	0.0	10.0	12.9	2.7	0.32	1	17	59.8
255	55	13.3	1.6	5.6	4.2	4.2	2.5	0.55			

ISSN 1929-7750 (online).