Towards Measurement of the Relationship between Student Engagement and Learning Outcomes at a Bricks-and-Mortar University

Carmel Kent*, Chris A. Boulton, Hywel Williams
University of Exeter, UK
c.kent,c.a.boulton,h.t.p.williams@exeter.ac.uk

Abstract. The relationship between student engagement and learning outcomes has been extensively studied in the context of online learning. However, it has been less investigated in face-to-face learning. In this paper, we describe initial findings from a study of student engagement and outcomes at a 'bricks-and-mortar' (BaM) university, where engagement is characterized by a diverse set of systems and agents, spanning both physical and digital spaces. We ask whether the substantial relationship often found in online environments between engagement and outcomes, holds in a BaM setting. We present initial analysis of data traces from various sources, each relating to a different dimension of engagement. Initial results indicate a weak relation between engagement and outcomes, suggesting that this important relationship may be substantively different in face-to-face/BaM and online learning environments. These preliminary findings highlight the need for further research, tackling challenges which are specific to face-to-face learning in a bricks-and-mortar university environment.

Keywords: Learning analytics · Bricks and mortar · Learning outcome · Engagement

1 Introduction

Student engagement and learning outcomes are amongst the most ill-defined and broadly interpreted theoretical concepts, for which there are no currently agreed upon frameworks for operationalization [2, 5]. This vagueness is one of the reasons for the general lack of clarity about the relation between them [16]. Nevertheless, the relationship between engagement and outcomes has been extensively investigated in the context of online learning, in which participation is shown to be highly correlated with various types of learning outcomes [1, 3-4, 7, 11, 20-22]. In purely online learning settings, engagement is typically defined narrowly in terms of student interactions with a Virtual Learning Environment (VLE), usually in the context of a specific course or module. However, student engagement in 'bricks-and-mortar' (BaM) institutions, where most teaching is delivered face-to-face, is much less clearly defined and there are associated difficulties in its measurement and analysis. Thus much less evidence is gathered in order to determine if and how engagement is of value for predicting outcomes in face-to-face learning.

Online learning is not analogous to face-to-face learning and each requires different conceptualization and operationalization frameworks [8, 12]. Moreover, students are shown to engage differently when learning in an online learning environment as opposed to BaM environment, also resulting in different learning outcomes. Specifically, this difference might be explained by the nature of online learning, which is more self-regulated [10]. Within a BaM environment, learners interact with a wide variety of systems, some of which relate directly to their course performance (e.g. lectures, assessments, VLEs) while others address learning outcomes in a wider context (e.g. career planning). Comparative study of higher education learning across different contexts and environments is still in its infancy [10] and holds many technical challenges relating to the collection, integration and ethical aspects of data from multiple sources [18]. In this paper, we present initial insights into the relationship between student engagement and learning outcomes in a BaM university. While trying to capture this relationship's flexible and sometimes elusive nature, here we adopt a holistic approach that aims to integrate data captured from various sources and interaction points in order to provide a multidimensional image of student engagement.

1.1 Measuring Engagement

The phrase "student engagement" has come to refer to the level of involvement students appear to have within their classes and their institutions in the context of learning [5]. Moore [14] proposed three types of interactivity: learner-content, learner-instructor and learner-learner. We suggest extending this framework and viewing students' engagement at a BaM institution as a multi-dimensional construct entailing the measurement of interactions between the student and various types of resources and agents (such as systems, people and devices) associated with the individual learning experience [19]. For our purpose, an interaction denotes a singular instance or event in which a student uses a resource, and represents a temporal relationship between the student and the resource [6]. For instance, an interaction may be attending a lecture, submitting a quiz, speaking to a lecturer, or accessing the VLE. It is very difficult to separate the net contribution of each type of interaction to the learning process. Even in the field of online learning, where interactions are easier to identify, this debate still remains open [5]. In addition, it is very complicated to study 'engagement' across different learning designs/goals and backgrounds of students.

Thus, in this paper, we execute an initial cross-design analysis, and add demographic parameters, in order to support future work with more fine-grained cohorts.

1.2 Measuring Learning Outcome

It is enormously challenging to measure the depth of understanding at a course-specific learning outcome [17, 19]. Module results usually include assessment tools that are defined by clarifying specific learning objectives [13]. There are important differences between face-to-face and online learning, including the pedagogical basis for assessment. Instructivism, which is common in BaM's face-to-face learning, maintains that knowledge should be transferred directly from the instructor to the learner without further interactions [15]. On the other hand, social constructivism is often implemented in collaborative online learning environments, whereby the teacher is seen as a facilitator between students, content and platforms, and social interactions are more central [9]. In accordance, the definition of learning outcomes might reflect on that difference, and thus face-to-face learning assessment in BaM institutions could be less correlated with interactive behaviors. While we recognize that there are many kinds of learning outcome, in this initial study we focus on student performance as measured by module grades.

2 Method

Engagement has been shown to correlate with performance in online learning. In this study, we ask how this relation manifests in a BaM university. More specifically, we attempt to determine what types of interactions and student characteristics can predict specific learning outcomes. Working with data from a traditional BaM university in the UK, we have collected data from various university systems for 30,781 undergraduate students across three academic years commencing in Autumn 2013, 2014 and 2015. Tables 1, 2 and 3 below summarize the variables extracted to operationalize engagement, demographic characteristics and learning outcomes respectively. The systems from which the variables are extracted, as well as basic descriptive statistics, are also presented. Our initial unit of analysis was the aggregate of all interactions involving a specific student in a specific year, resulting in a dataset of 52,553 records.

Table 1. Engagement variables and data sources

Variable	System	Missing	Mean	St Dv
Number of attended career events	Career Events System. Events are optional and cover a wide range of topics.	0	1.60	2.88
Number of signed-up career events	Career Events System	0	1.99	3.34
Proportion of career events signed-up to that were attended	Careers Events System	0	0.46	0.46
Number of logins	Virtual Learning Environment (VLE)	0	79.72	68.83
Number of logins	Inter Library Loans (Library ILL). Online access to borrow books from other UK libraries.	0	0.00	0.63
Number of logins	Library. Online access to academic journals and e-resources and manage library resource loans.	0	0.19	0.70
Number of library's fines paid	Library	0	0.12	0.54
Number of logins	MACE (Module and Course Evaluation) system. An optional quality questionnaires for students.	0	1.17	1.45
Number of submitted evaluations	MACE	0	0.83	1.07
Number of logins	Exam's archival system	0	3.29	6.64
Number of papers' views	Exam's archival system	0	15.35	28.20
Number of all interactions	All systems (VLE, Library ILL, Library, MACE, Exam's archival system)	0	100.66	87.66
Number of committee interactions	Student's guild (buying tickets to guild's events, holding positions on volunteering project committees)	0	0.03	0.18
Number of enrolled programs	Registration system	0	1.07	0.26

Table 2. Demographics variables and data sources

Variable	System	Missing	Type	Dominant category
Gender	Registration system	30	Categorical	Female 55.1%
Disability (type of disability)	Registration system	72	Categorical	No known disability 87.2%
National identity	Registration system	5,700	Categorical	British 41.3%
Nationality	Registration system	1,584	Categorical	UK 69.8%

Country of domicile	Registration system	56	Categorical	England 69%
Ethnicity	Registration system	1,595	Categorical	White 73.9%
Age at enrollment to the university	Registration system	265	Numerical	Mean: 19.80
Age at the beginning of the year	Registration system	256	Numerical	Mean: 21.04
Living away from home	Registration system	0	Binary flag	Away: 72.6%
Parents' occupational background	Registration system	6,339	Categorical	Higher managerial 23.2%

Table 3. Outcome variables and data sources

Variable	**System**	**Missing**	**Mean**	**St Dv**
Average number of attempts for all modules in a year	Module Assessment	2,814	1.01	0.09
Average results for all modules in a year, normalized by credits' weights (i.e. summative 'end of year result')	Module Assessment	8,106	49.80	21.31
Number of failures in all modules in a year	Module Assessment	7,697	0.15	0.84
Number of pass grades in all modules in a year	Module Assessment	7,697	4.21	2.70
Proportion of passes out of all passes and failures	Module Assessment	7,697	0.96	0.16
Number of results which were not agreed in a year	Module Assessment	0	0.07	0.31
Number of agreed upon results in a year	Module Assessment	0	6.84	2.77
Average gap between module result and its class average	Module Assessment	8,106	0.003	2.64

3 Findings

Here we present our two-step analysis. First, we present the significant pairwise relations found between outcome variables, and engagement or demographics variables. Second, we present a multivariate model to try and predict student success based on features found to be significantly correlated with outcome at our first step.

3.1 Pairwise Relations between Outcome, Demographics and Engagement

Since none of our outcome variables are normally distributed, we used Spearman's rank correlation test to find significant relationships between them and any numeric engagement variable. A quick exploration of the engagement variables shows that VLE logins, Past Exam views, Library logins, MACE submissions and event attendances follow a typical power law distribution as one might expect, where many students use each individual system sparingly and few students use each system often. When correlating outcome with categorical variables, we have used Mann-Whitney U test and Kruskal-Wallis H test. For space limitations, we only show significant relations with the normalized result outcome variables, we are omitting significant relations which were found to be very weak, in addition to some of the post-hoc results.

Table 4. Pairwise relations between average results for all modules in a year, normalized by credits' weights variables and between demographics and engagement variables.

Significant demographic variables	**Selected post-hoc results**	**Engagement variables**
Gender U = 231120953.50**	Female (Med= 60.16)>Male (Med = 57.03)	MACE- logins (r = 0.262)** MACE-Submitted evaluations (r = 0.250)**
Away from home U= 152140073.00**	Away(Med = 60.25)>Local(Med = 52.01)	
Disability H(10) =168.02**	Long standing illness, Mental health, Mobility issues, learning difficulty > Information refused	
Is Disable flag H(3)=73.89**	Refused >No disability>Disability	
Country of domicile H(140)=1,554.98**		
Ethnicity H(18)=627.97**	White>Arab, Asian, Black	
National identity H(7)=360.69**		
Nationality H(187)=1,880.03**		
Parents' occupational H(326)=869.74**	All managers > All routines roles	

*Correlation/ difference is significant at the .05 level (two-tailed test) **; significant at the .01 level or below (two-tailed test)

3.2 Multivariate Model to Predict Outcome out of Demographics and Engagement

For our regression model, we used the 'logged' version of some of the numeric variables in an attempt to make them more normally distributed, which while helpful has not fully solved the problem of non-normality. As there are some students who have not accessed some of the systems at all, we make the transformation x -> log(x+1) which maps 0 to 0 and prevents the problem of trying to use log(0). We have fitted a model to predict the weighted average results for a year, resulting ($F(11, 44425) = 512.7$, $R^2 = 0.1126$, Adjusted $R^2 = 0.1124$), $p< 2.2e^{-16}$, Residual standard error=20.08. The parameter estimates and significances are detailed in Table 5 below.

For the categorical variables in the table, the first factor that appears in the data is assumed to have a coefficient of 0 (e.g. “Female” has no effect on our model) and other factors for that category are assigned a coefficient of which the significance is then determined.

Table 5. Multivariate model parameters and significances (engagement variables are in bold)

Coefficients	**Estimate**	**Std. Error**	**t value**	**p-value**
(Intercept)	52.446	0.823	63.751	$<2*10^{-16}$ **
Gender (Male)	-0.239	0.19286	-1.242	0.2143
Age at beginning of year	-0.328	0.035	-9.399	$<2*10^{-16}$ **
Away from home	5.973	0.224	26.616	$<2*10^{-16}$ **
Disability Type (Unknown)	2.107	1.936	1.088	0.2764
Is Disable (Yes)	-2.834	0.284	-9.978	$<2*10^{-16}$ **
log(events attended + 1)	2.832	0.132	21.495	$<2*10^{-16}$ **
Committee interactions	8.914	0.489	18.215	$<2*10^{-16}$ **
log(VLE + 1)	-1.944	0.085	-22.870	$<2*10^{-16}$ **
log(Past exams + 1)	0.130	0.067	1.937	0.0528 *
log(Library logins + 1)	4.842	0.302	16.009	$<2*10^{-16}$ **
log(MACE + 1)	9.224	0.187	49.364	$<2*10^{-16}$ **

*Coefficient is significantly different from 0 at the .1 level. **Coefficient is significantly different from 0 at the $<2*10^{-16}$ level or below

Our model appears to struggle from there being a low number of high scores in the dataset. Generally, we find that being male and older is likely to reduce your assessment results, as is living at home and being disabled. It also appears that being ‘more engaged’ is beneficial, except apparently logging onto the VLE too much could be a disadvantage for the overall result.

4 Conclusions

One of the major challenges of learning analytics in a BaM setting is the need to integrate analytics across different spaces and tools. In this study, we describe initial steps into exploring the relationship between learning outcome and engagement variables, where measures about engagement are integrated from students' interactions with a variety of systems and services, physical and digital. In addition, we have added demographic variables to be able to easily identify finer grained cohorts for further analysis. Following the collection and integration phase, we have shown here a regression model, predicting the aggregative score of all module grades at the end of the year. Our model shows the predictive values of demographics variables such as age, disability and being away from home, along with engagement variables, showing interactions with some of the university's systems and services, partially supporting existing evidence of the relation between engagement and outcome. Interestingly, most of the significant estimates were shown with systems which are not directly related to learning, but rather with a wider framework of interactions held between students and the university facilities, such as career events, committee activities and quality questionnaires. Moreover, interactions with the VLE, the digital system which coordinates most learning activities, were shown to be negatively correlated with module grades. Taking into consideration that the VLE, as well as library resources, are not used equally or standardly across all modules, this requires further investigation.

4.1 Limitations and Future Work

A problematic aspect for utilizing our findings is the observed range of residuals in the modelling exercise. For example, this could suggest that using a predictive modelling technique to determine failing students is unlikely to be effective, at least when using a student per year timescale and seeing how an individual student's performance changes over time. We could hopefully explain more variance by reducing this to a termly timescale. Module assessments are usually derived directly from different learning objectives and designs [13]. This variation could further cause a differentiation in the dependencies on different systems. The importance of module assessments in the total aggregative score also varies. Thus, a more predictive model could result from analyzing students enrolled to a specific module, course or programme. Age was shown to negatively affect the outcome. In addition to the reported relations above, when exploring secondary relations, among engagement and demographic variables, the age's negative relations with some engagement variables (such as all interactions with digital systems and career events attendance) suggests an explanation to this negative effect, and is subject to further analysis. In addition, some positive correlations among the engagement variables themselves (such as VLE logins, MACE, exams' archive and all digital interactions) supports the notion that "students who do stuff also do more stuff".[1]

Traditional approaches of the teaching-centered paradigm are usually measured by summative scores. Nonetheless, an educational institution's definition of learning outcomes, as well as the subjective expectation each student adopt, does not necessarily adhere to the taken summative measurements. Some students are after First Class Honors while others are aiming simply to complete the course or find a decent career. Therefore our goal should be to enable a flexible, multi-dimensional, possibly sometimes subjective framework for 'learning outcomes', and to seek to find

---

1 http://blogs.edweek.org/edweek/edtechresearcher/2014/03/big_data_mooc_research_breakthrough_learning_activities_lead_to_achievement.html

relations between various dimensions of engagement, demographics and various dimensions of learning outcome. For example, adding data from surveys (or other sources) could broaden our current limits of the data by complementing it with students' self-perceived interactions, data about their face-to-face interactions with each other or with their instructors, informal interactions (such as interacting over social media), their own perceptions about what is considered to be their 'learning outcomes' and more. In addition, some of our current variables are too coarse. For example, adding finer grained VLE activities, such as posting on a bulletin board and downloading material, separating data about career events' attendance by the event type and more, are crucial and can benefit our overall understanding about students' engagement.

5 References

[1] Adeyinka, T., & Abdulmumin, I. (2011). Pattern of undergraduate's participation in the online discussion forum at the Univeristy of Ilorin, Nigeria. *Management, Journal of Information Technology*, *12*(3), 59–76.

[2] Akyol, Z., & Garrison, D. R. (2011). Understanding cognitive presence in an online and blended community of inquiry: Assessing outcomes and processes for deep approaches to learning. *British Journal of Educational Technology*, *42*(2), 233–250. http://doi.org/10.1111/j.1467-8535.2009.01029.x

[3] Andresen, M. A. (2009). Asynchronous discussion forums: success factors, outcomes, assessments, and limitations. *Educational Technology & Society*, *12*(1), 249–257.

[4] Asterhan, C. S. C., & Hever, R. (2015). Learning from reading argumentive group discussions in Facebook: Rhetoric style matters (again). *Computers in Human Behavior*, 53, 570-576. http://doi.org/10.1016/j.chb.2015.05.020

[5] Axelson, R. D., & Flick, A. (2010). Defining Student Engagement. *Change: The Magazine of Higher Learning*, *43*(1), 38–43. http://doi.org/10.1080/00091383.2011.533096

[6] Brooks, C., Thompson, C., & Teasley, S. (2015). A time series interaction analysis method for building predictive models of learners using log data. *Proceedings of the Fifth International Conference on Learning Analyticsand Knowledge - LAK '15*, 126–135. http://doi.org/10.1145/2723576.2723581

[7] Cerezo, R., Sánchez-Santillán, M., Paule-Ruiz, M. P., & Núñez, J. C. (2016). Students' LMS interaction patterns and their relationship with achievement: A case study in higher education. *Computers & Education*, *96*, 42–54.

[8] Deboer, J., Ho, A. D., Stump, G. S., & Breslow, L. (2014). Changing "Course": Reconceptualizing Educational Variables for Massive Open Online Courses. *Educational Researcher*, http://doi.org/10.3102/0013189X14523038

[9] Garrison, D. R. (2006). Online collaboration principles. *Journal of Asynchronous Learning Networks*, *10*(1), 25–34. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.96.4536&rep=rep1&type=pdf

[10] Harris, R., & Nikitenko, G. (2014). Comparing online with brick and mortar course learning outcomes An analysis of quantitative methods curriculum in public administration. Teaching Public Administration, 32(1), 95–107. http://doi.org/10.1177/0144739414523284

[11] Kuzilek, J., Hlosta, M., Herrmannova, D., Zdrahal, Z., & Wolff, A. (2015). OU analyse: Analysing at-risk students at The Open University. *Learning Analytics Review*, 1-16.

[12] McConnell, D. (2000). Implementing computer supported cooperative learning. In Millar, R. (2013). Improving science education: Why assessment matters. *Valuing Assessment in Science Education: Pedagogy, Curriculum, Policy*, 55–68, Psychology Press.

[13] Millar, R. (2013). Improving science education: Why assessment matters. *Valuing Assessment in Science Education: Pedagogy, Curriculum, Policy*, 55–68.

[14] Moore, M. G. (1989). Editorial: Three types of interaction. *The American Journal of Distance Education*, *3*(2), 1–6.

[15] Onyesolu, M. O., Nwasor, V. C., Ositanwosu, O. E., & Iwegbuna, O. N. (2013). Pedagogy: Instructivism to Socio-Constructivism through Virtual Reality. *International Journal of Advanced Computer Science and Applications*, *4*(9), 40–47. Retrieved from http://ijacsa.thesai.org/

[16] Picciano, A. G. (2002). Beyond student perceptions: Issues of interaction, presence, and performance in an online course. *Journal of Asynchronous Learning Network*, *6*(1), 21–40.

[17] Prince, M. (2004). Does Active Learning Work ? A Review of the Research. *Journal of Engineering Education*, *93*(July), 223–231. http://doi.org/10.1002/j.2168-9830.2004.tb00809.x

[18] Reyes, J. A. (2015). The skinny on big data in education: Learning analytics simplified. *TechTrends*, *59*(2), 75–80. http://doi.org/10.1007/s11528-015-0842-1

[19] Shavelson, R. J., & Huang, L. (2003). Responding Responsibly. *Change: The Magazine of Higher Learning*, *35*(1), 10–19. http://doi.org/10.1080/00091380309604739

[20] Song, L., & McNary, S. W. (2011). Understanding students' online interaction: Analysis of discussion board postings. *Journal of Interactive Online Learning*, *10*(1), 1–14.

[21] Wei, H., Peng, H., & Chou, C. (2015). Can more interactivity improve learning achievement in an online course? Effects of college students' perception and actual use of a course-management system on their learning achievement. *Computers & Education*, *83*, 10–21. http://doi.org/10.1016/j.compedu.2014.12.013

[22] Zhu, E. (2006). Interaction and cognitive engagement: An analysis of four asynchronous online discussions. *Instructional Science*, *34*(6), 451–480. http://doi.org/10.1007/s11251-006-0004-0

Acknowledgments

This research was supported by the Effective Learning Analytics Project at the University of Exeter. A project which aims to help students reach their full academic potential while studying at Exeter.