Analysing the learning pathways of students in a large flipped engineering course

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Recent advancements in educational technologies (learning management systems, online discussion forums, peer-learning tools) coupled with new methods of course delivery (e.g. blended, flipped, MOOCs) provide significant opportunities for universities to deliver challenging, high quality, yet engaging curriculum for students. In this paper, we examine the variations and similarities of student's approaches to learning (learning pathways) by examining how well they performed in a large (N ~ 1000 student) first year engineering flipped classroom. The analysis focused on student's performance in their assessment (formative and summative) as well as their online interaction with a range of tools purposely built to support students through peer learning and acquisition of resources and expertise. Analysis using k-means clustering reveals that students do in fact adopt a variety of successful pathways through the course. The unique aspects of this work lie in the use of analytics algorithms that whilst perhaps routinely utilised in data mining, are not as well utilised in better understanding patterns (successful or otherwise) of student interactions within a technology enhanced active learning environment that integrates theory with engineering practice.

Introduction

There is a growing body of research about how students interact with online and blended learning pedagogies. These began with early understandings of the potential of distance education (Moore, 1989, 1990), to how online learning could foster a community of inquiry (Anderson & Garrison 1997; Garrison, Anderson & Archer 2000). However, what has sometimes been lacking is an evidence-based approach to learning analytics that supports learners and staff (Kruse & Pongsajapan, 2012; and that is based on learning design, and behavioural, social and cognitive measures of engagement. It also requires the development of learning analytics that tell us with useful information about students' progress through their studies (Long & Siemens 2011). The significance of this work is that it takes a more diverse view of learning analytics, built along solid learning design principles and utilises data generated during student learning activities to contribute to student facing learning analytics as well as providing meaningful data for staff. The following sections outline engagement, learning analytics and the learning design approach taken.

Literature review

There has been some criticism of learning analytics as favouring behaviourist measures over more complex and nuanced understandings of learning (Siemens and Long,). Mamun, Lawrie and Wright (2016) define *engagement* in behavioural terms as "student participation, effort, attention, persistence and positive conduct towards the learning activity" (p. 381). Defining student engagement in purely behaviourist terms is inconsistent with the approach proposed by Wiseman, Kennedy and Lodge (2016), where it is defined as "students' active involvement or deliberate investment of effort in their educational activities" (p. 666). Wiseman, Kennedy and Lodge (2016) reinforce the notion that engagement cannot be seen in strictly behaviourist terms and must comprise cognitive, affective and behavioural dimensions. This latter definition characterises the sense in which the term is used in this paper.

The learning analytics research tends to focus on how student interaction is linked to *performance*. Performance from a learning analytics perspective is usually seen in terms of retention or grade achieved (Davies & Graff, 2005; Yu & Jo, 2014) however it can be measured in terms

of course completion (Breslow et al., 2013). Davies and Graff (2005) found that there was little difference in performance (measured as grades) based on student participation in an online discussion forum. The exception to this was failing students, whose interactions were very low. Yu and Jo (2014) identified four variables that were predictive of student success or performance (time using the LMS; interaction with peers; regularity of access of LMS; and number of downloads). These four variables accounted for 33.5% of the variance in the final grade but tend to have a focus on behavioural analytics. Breslow et al. (2013) similarly used time spent on resources as a measure of student engagement leading to success (in this case obtaining a certificate of completion for a MOOC course). The resources investigated included videos, problem solving, online laboratories, and a discussion forum.

However, Kuo, Walker, Schroder and Belland (2014) found that learner-instructor and learner-content interactions were predictors of student success but learner-learner interactions were not. Additionally, Lam and Muldner (2017) found that cognitive engagement leads to better learning outcomes, especially where that task is collaborative. Viewing performance in narrow terms risks providing incomplete information to either staff or students about their possibility of a student doing well in the course of study. These findings seem to indicate that technology enhanced, active learning environments that seek to develop social skills may be ineffective if they do not sufficiently support the needs of student's collaborative efforts to complete assessment tasks.

On the other hand, Tempelaar, Rienties and Giesbers (2015) found that student performance on formative assessment tasks was a stronger predictor of student performance than time spent using the LMS (e.g. such as using clickstream data). Scheffel et al. (2017) found that the number of posts made in a discussion forum was a better predictor of performance than time spent online per se. Scheffel et al. (2017) advocate for the use of learning analytics that are skills based and that support learners whilst they are engaged in the course. This would lend itself to an approach where students are supported to learn interpersonal skills, intra-personal understandings and other practice based skills, whilst still linking them firmly with disciplinary practice. This leads to the necessity to identify suitable student-facing learning analytics and how best to present them (Verbert et al., 2014).

Providing students with information about their own learning practices and might enable them to make decisions regarding how to be successful themselves and how to gauge their current levels of success. This tends to support the (seemingly common sense) notion that the learning environment itself, and therefore the learning design may have a greater influence on the actions required for genuine success than a poorly thought out online learning presence. It also suggests that a range of measures are likely to be predictive of success and that there is a need to investigate more complex and nuanced ways of understanding student progress, particularly in authentic technology enhanced active learning oriented courses. This brief survey of the research literature leads to the identification of a range of indicators that might be provided to students in the form of dashboards and visualisations.

Learning context

Engineering Modelling and Problem Solving or ENGG1200, is a large (approximately 1000 students) second semester first year course, originally implemented in 2012. This course has been modified over the past 5 years in response to staff and student needs. The course is designed to introduce students early to the concept of what it is like to work as an engineer on complex, ill-defined problems. In this case students have the choice to complete either an aircraft prototype (such as a glider with landing beacon) or a process control system (treatment of water using a regent activated at a certain temperature).

The pedagogical design of the course is heavily influenced by the community of inquiry framework proposed by Anderson and Garrison (1997), and Garrison, Anderson and Archer (2000). An adapted version of this framework is presented in Figure 1. The course utilises a flipped classroom approach. Flipped classrooms can take a variety of forms. However, generally in class time is devoted to active learning and time outside of class is spent completing asynchronous tasks such as watching videos and completing practice quizzes. In adopting this model for ENGG1200, the course has no face-to-face lectures and consists of 5 hours of active learning workshops. Additionally students spend an equal amount of time (over the first six weeks of the course) completing online learning activities aimed at supporting students to engage with content (Materials Science) through videos, readings and Blackboard multiple choice (MCQ) formative and low stakes summative concept quizzes (McCredden, Reidsema & Kavanagh, 2017; Reidsema, Kavanagh & McCredden 2016; Kavanagh & Reidsema 2014). An added consequence and challenge of Blended or Flipped Classrooms at this scale involves solving the problem of motivating and developing what is termed "agency" or "self-regulation". Agency is not only a critical aptitude for success in academia as well as industry. A high level of "student ownership of learning" (Lave & Wenger, 1991) is essential in order to successfully navigate courses such as ENGG1200 where learning is "authentic" involving complex technological and interpersonal problem solving

(Mamum, Lawrie & Wright 2016). Student ownership of learning is a key part of ENGG1200.

Because there are no lectures a "digital ecosystem" has been developed to support student learning. Since 2013, we have trialled and incorporated Facebook for Schools but develop Casper Q&A, (a novel student mediated discussion tool) in an effort to mitigate the loss of social presence that might otherwise be provided by the lecture activity (Smith et al., 2013). Additionally, the consequences of this type of course design with such large numbers of students are that there is a loss of "feel" for how well students are engaging as well as performing in various elements of the course. The tools are also designed to support students to develop reflective writing and professional development goals (Reflection tool), critical thinking (MOOCchat), group work measured using the Peer Assessment Factor (through the PAF tool) and problem solving skills (PSS, which forms part of the group design project). The assessment incorporates summative and formative assessment tasks (templates, memo, online quizzes, mid semester exam, project report). The approximate relationship of the tools and assessment is shown in figure 1). Students can also make use of the Learning Pathway tool (Reidsema, Kavanagh, Fink, Long & Smith 2014) to keep track of their completion of tasks and assessments throughout the semester. The data gathered from these online tools, including clickstream data could be used to generate information of relevance to the large teaching team and to the students themselves. Currently, information is presented to students in the form of a dashboard.

Figure 1: Integration of assessment aims and online support tools for authentic flipped learning

Methodology

Approach

Available scores capturing the class raw data of the 832 students registered in the course are presented in Figure 2. Students are graded on a seven-point scale where 7 is a high distinction, 6 a distinction, 5 a credit, 4 a pass and grades below 3 are failing grades. L_i represents available scores for students that have received a final grade of between 3 and 7. In addition, L is organised into 3 sub-tables: S with feature $S_1 \ldots S_s$, represent scores that illustrate performance of the students in summative assessments, F with features $F_1 \ldots F_f$, represent scores that illustrate performance of the students in formative assessments, and E with features $E_1 \ldots E_e$, represent scores that approximate students' engagement with different tools.

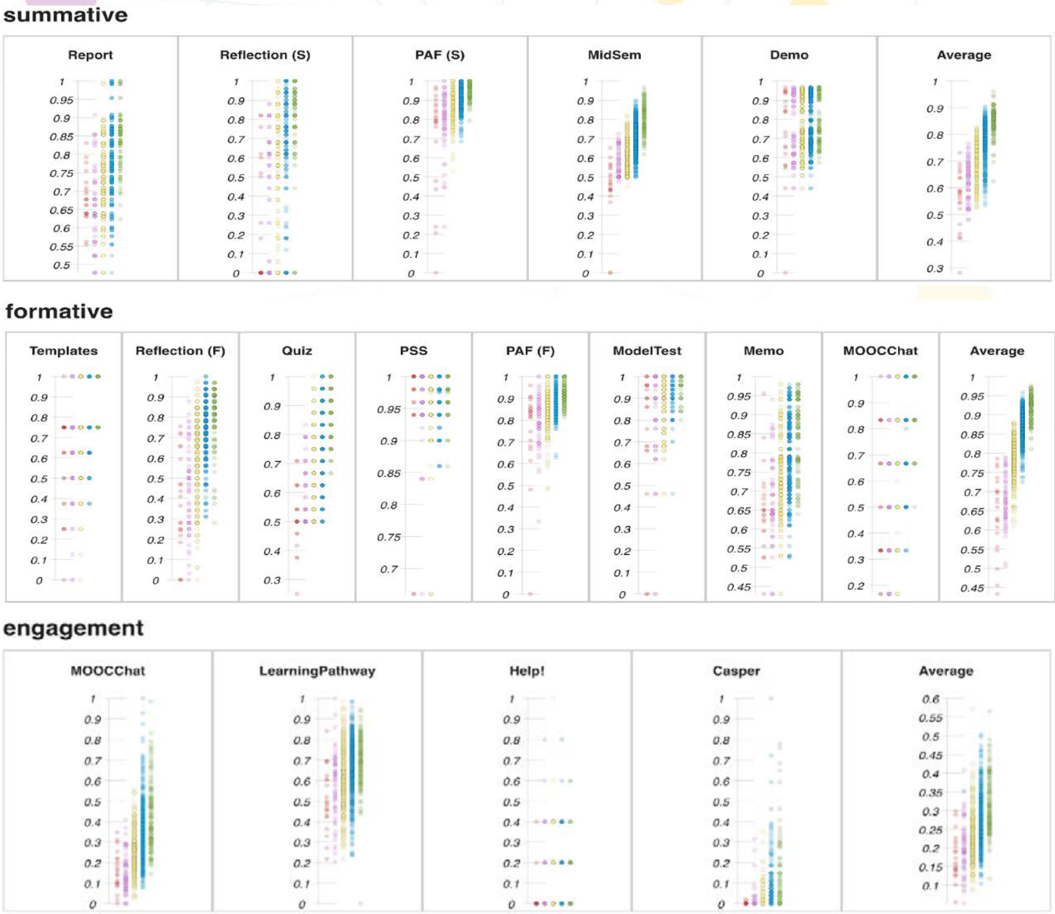


Figure 2 demonstrates a snap shot of the learning dashboard visualising the grade and engagement distribution of students with each course grade across different tools and assessments. In this dashboard, the following colour-coding is used for grades: green=grade of 7, blue= grade of 6, yellow= grade of 5, pink= grade of 4, and orange = grade of 3

Data organisation

Data from 832 students are included in this study. For each student, a total of 53 available scores are used to compute a set of 16 features. **S** features are organised into S_1 (Demo Day), S_2 (Reflections), S_3 (Mid-Semester Exam), S_4 (Final Report), S_5 (PAF 2). $S_{average}$ represents the average score across all formative features. **F** features are organised into F_1 (Templates), F_2 (Problem Solving Sheets), F_3 (Online Quizzes), F_4 (Moocchat), F_5 (Preliminary Memo), F_6 (Model Test), F_7 (PAF 1). $F_{average}$ represents the average score across all formative features. **E** features are organised as follows as E_1 (Percent of item accesses for each week in the Learning Pathway tool), E_2 (Number of posts in the MOOCchat tool), E_3 Number of tickets opened in the Help! tool, E_4 (Number of question views in the Casper tool. Al results were normalised to between and 1. $E_{average}$ represents the average score across all engagement features.

Results

Clustering

An established clustering algorithm, k-means (Khosravi & Cooper, 2017), has been employed to investigate and reveal patterns of learning and engagement in sub-populations of students with the same final course-grade. We determined values for the range of K using the "elbow" method (Khosravi & Cooper, 2017), which can be traced back to (Thorndike, 1953). This method aims to obtain the number of clusters by computing and plotting the sum of square errors (SSE) for a range [MIN..MAX] of values of K. The goal is to manually choose a K at which the marginal gain drops significantly, producing an angle (elbow) in the graph. To account for the random initialization of centroids in k-means, the recommendations of Ferguson and Clow (2015) are followed; for each value in the range, 100 executions of the k-means algorithm are run and the solution with the highest likelihood is recommended. (The high level code for performing this analysis can be found in Appendix 1.)

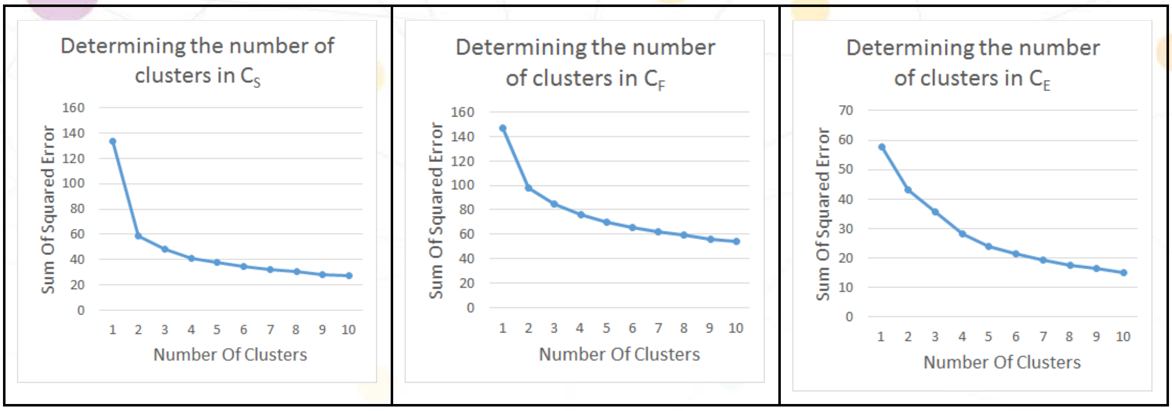


Figure 3: Using the elbow method for determining K_S, K_F, and K_E

Clustering Based on Summative Assessments

The results obtained from running k-means with four clusters identified as C_{S1}, C_{S2}, C_{S3}, and C_{S4} on **S**, which captures the performance of the students in summative assessments, are reported in table 2. Clusters are ordered based on $S_{Average}$, which captures the average performance of members of a cluster across all of the summative assessments.

Table 2: Using k-means to cluster the students based on their summative assessments. S_1 (Demo Day), S_2 (Reflections), S_3 (Mid-Semester Exam), S_4 (Final Report), S_5 (PAF 2), $S_{average}$ (average of S_1 … S_5)

Name	N	S_1	S_2	S_3	S_4	S_5	$S_{average}$
C_{S1}	229	**0.929**	0.769	0.692	0.793	0.907	**0.818**
C_{S2}	222	0.693	**0.829**	**0.756**	**0.797**	**0.925**	0.800
C_{S3}	174	0.668	0.669	0.594	0.720	0.863	0.703
C_{S4}	207	0.799	0.354	0.617	0.742	0.850	0.672

C_{S1} and **C_{S2}** could be said to be good all round performers (with 229 and 222 students in each of these clusters respectively). What distinguishes these two groups is their performance on the Demo Day, the Mid-semester exam and their PAF2 scores. These two groups have the highest performance based on $S_{Average}$ however, **C_{S2}** students appear to dominate teamwork sessions based on their higher S_5 (PAF) scores, they also score considerably higher than other students on their reflective pieces. The main factor that separates C_{S1} members from those in other groups is their high grades on the demo day (S_1). They are also doing well on S_4 and S_5; however, compared to members in C_{S2} who appear to be strong individual performers, their S_2 and S_3 grades are relatively lower.

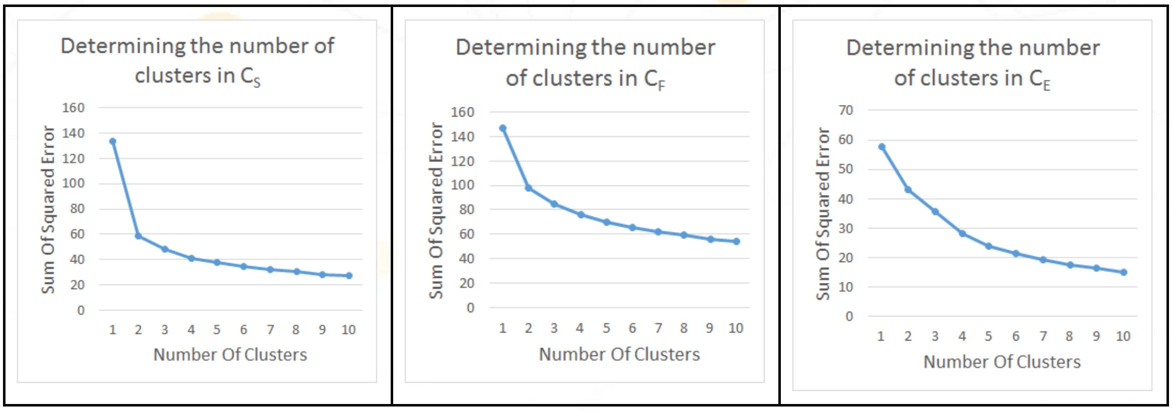
The solid performers in C_{S3} consists of 174 students who have the second lowest performance based on $S_{Average}$. They have the lowest average grade on S_1, S_3, and S_4, suggesting that overall, they are performing poorly on both individual and team-based assessments.

C_{S4} consists of 207 students who have the **lowest performance** based on $S_{Average}$. Although their performance is better than members in C_{S3} on the majority of the summative assessments, their very low grade or failure to complete the Reflections (S_2) puts them in the lowest performing cluster. This cluster also has the lowest average grade on S_5, indicating that on average they are seen as the lowest contributors to the teamwork component.

Clustering Based on Formative Assessments

The results obtained from running k-means with four clusters identified as C_{F1}, C_{F2}, C_{F3}, and C_{F4} on **F**, which captures the performance of the students in formative assessments, are reported in table 3. Clusters are ordered based on $F_{Average}$, which captures the average performance of members of a cluster across all of the formative assessments.

Figure 3 demonstrates the sum of squares error for 1 to 10 clusters for C_S, C_F, and C_E (these clusters are described in more detail later in this section.) The elbow method attempts to find clusters that have the properties of internal cohesion and external separation. However it is challenging to find an appropriate number of clusters based on student populations that are scattered across the feature space, resulting in over-fitting or under-fitting the data. In this example, the recommended value for K_S, and K_F, is 2 and possibly 3 for K_E. However this results in an under-fitted data set. McKelvey (1975, 1978, cited in Ketchen & Shook, 1998) recommends considering as many variables as possible when using an inductive, exploratory approach as it is not possible to ascertain which variables will identify differences among observations. As such, despite the recommendation, since this is an exploratory study, we used the elbow method to give us a ballpark figure for the minimum number of clusters and chose 4 clusters in each case to have the ability to perform a more in-depth analysis.



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Name	N	F_1	F_2	F_3	F_4	F_5	F_6	F_7	$F_{average}$
C_{F1}	368	0.992	**0.997**	**0.829**	**0.959**	**0.790**	**0.964**	**0.892**	**0.915**
C_{F2}	149	**0.995**	0.975	0.690	0.674	0.765	0.953	0.853	0.844
C_{F3}	215	0.690	0.970	0.691	0.813	0.764	0.930	0.859	0.817
C_{F4}	100	0.580	0.973	0.580	0.412	0.714	0.865	0.806	0.704

C_{F1} consists of 368 students who have the highest performance based on $F_{Average}$. Except for F_1, they have the highest average grade on all of the formative assessments. In particular, they have a much higher average grade in F_3 and F_4 compared to the other clusters.

C_{F2} consists of 149 students who have the second highest performance based on $F_{Average}$. They have the highest average grade for F_1 and the second highest average across most of the other formative assessments. An interesting note is that their average F_4 grades is much lower than both members from C_{F1} and C_{F3}, suggesting that these students do relatively well on all of the formative assessments except the online quizzes.

C_{F3} consists of 215 students who have the second lowest performance when averaged across formative assessments. Their lower F_1 and higher F_4 score seem to be their differentiating factor from members clustered into C_{F2}.

C_{F4} consists of 100 students who have the lowest performance when averaged across formative assessments. Except for F_2, they have the lowest average grade on all of the formative assessments. In particular, their F_1, F_3, and F_4 scores are significantly lower than members of all of the other clusters.

Clustering based on online engagement

The results obtained from running k-means with four clusters identified as C_{E1}, C_{E2}, C_{E3}, and C_{E4} on **E**, which approximates engagement of the students, are reported in table 4. Clusters are ordered based on $E_{Average}$, which approximates the average engagement of members of a cluster across all of the available tools in the course. Roughly 70% of the students have not used E_4 at all, and approximately 5% of the students have used it extensively, viewing many of the questions that are asked on Casper. This explains why average engagement with E4 is low in all of the clusters.

Table 4: Using k-means to cluster students based on engagement. E_1 (Learning Pathway), E_2 (MOOCchat), E_3 (Help!), E_4 (Casper), E_e (Average of E_1…E_4)

Name	N	E_1	E_2	E_3	E_4	E_e
C_{E1}	100	0.705	0.298	**0.316**	0.049	0.342
C_{E2}	168	0.699	**0.532**	0.024	**0.069**	0.331
C_{E3}	326	**0.714**	0.258	0	0.040	0.253
C_{E4}	238	0.466	0.227	0.018	0.008	0.180

C_{E1} consists of 100 students who have the highest engagement based on $F_{Average}$. They have the highest average engagement with E_3 and have the second highest average engagement with all of the other tools.

C_{E2} consists of 168 students who have the second highest engagement based on $F_{Average}$. They have the highest average engagement with E_2, indicating that most students in this cluster take a leading role in MOOCchat discussions. They also have the average engagement in E_4 and the second highest average engagement with E_3.

C_{E3} consists of 326 students who have the second lowest engagement based on $F_{Average}$. Despite their low overall engagement, they have the highest average engagement with E_1, indicating that most students in this cluster are pro-active on the Learning Pathway. Interestingly their average E_3 score is 0, illustrating that none of the students in this cluster have ever sought help!

C_{E4} consists of 238 students who have the lowest engagement based on $F_{Average}$. Apart from their overall low engagement, they also have the lowest average engagement on almost all, except E_3, of the individual tools, indicating that they mostly take a passive role in the course.

Analysing the learning pathways of students with a similar course-grade

Table 5 illustrates the membership of students with a similar course-grade (3 – 7) with reference to their associated clusters in C_S, C_F, and C_E, and Figure 2 demonstrates a snapshot of the learning dashboard visualising the grade and engagement distribution of students with each course grade across different tools and assessments.

Table 5: Membership of students with a similar course-grade with reference to their associated clusters in C_S, C_F, and C_E

L_i	Size	C_S				C_F				C_E			
		C_{S1}	C_{S2}	C_{S3}	C_{S4}	C_{F1}	C_{F2}	C_{F3}	C_{F4}	C_{E1}	C_{E2}	C_{E3}	C_{E4}
L_7	121	0.39	0.58	0.00	0.03	0.88	0.06	0.06	0.00	0.12	0.46	0.34	0.08
L_6	385	0.33	0.37	0.14	0.16	0.58	0.19	0.21	0.02	0.11	0.26	0.43	0.20
L_5	245	0.21	0.05	0.37	0.37	0.16	0.26	0.42	0.16	0.13	0.05	0.38	0.44
L_4	60	0.02	0.00	0.37	0.62	0.0	0.05	0.28	0.67	0.16	0.00	0.37	0.47
L_3	21	0.00	0.00	0.24	0.76	0.00	0.05	0.29	0.67	0.05	0.00	0.29	0.67

L_7 constitutes of 121 students (14%) of the class population. The highest achieving students have mixed patterns of engagement, and summative results, but more distinct formative result membership. Their distributed memberships to C_{S1} and C_{S2} show that they either perform extremely well on both their individual summative assessments and group summative assessments or mostly on their group summative assessments. The distribution of formative features shows a strong alignment to C_{F1}, indicating that the students in L_7 consistently achieve the best results in all formative assessment items. L_7 membership strongly aligns to C_{E2} and C_{E3}, with a small population belonging to C_{E1}, and less than one percent hardly engaging at all. The C_{E2} membership shows that 46% of these students taking a leading role in MOOCChat and are highly engaged with Casper. On the other hand the C_{E3} membership shows that 33% of these students primarily engage with The Learning Pathway without utilising the other tools. Interestingly, 11% of these students, despite doing extremely well, have reached out and asked for help.

L_6 constitutes of 385 students (46%) of the class population. Students in this cluster have mixed summative and engagement memberships, with less varying formative memberships. The distribution between C_{S1} and C_{S2} shows that some of these students perform extremely well on their respective group or individual assessment items, with the less prominent memberships to C_{S3} and C_{S4} indicating that there were students who have poorer team workload distribution, or worse individual assessment achievements and thus inferior summative assessment results. The divided memberships between C_{F1}, C_{F2}, and C_{F3} indicate that L_6 consistently perform well on the formative assessments, however the close split between C_{F2} and C_{F3} shows that some students drop marks on the *Templates* (Individual), but make up for these lost marks in *MOOCchat* (Team)*,* or vice-versa. L_6 has varied membership features, indicating that each student found their own pathway to success with the tools. C_{E1} membership indicates that these students had a good balance of using each tool, whereas C_{E3} membership shows that some students achieved with relative little use of the *Help!* tool. Membership to C_{E2} shows that 26 percent of students found success through leading discussions in *MOOCchat*, and not valuing the use of *Casper*. The remaining population in C_{E4} is indicative of students who had very little engagement, but still succeeded in the course.

L_5 constitutes 245 students (29%) of the class population. Summative student features in this cluster distribute mostly evenly between C_{S1}, C_{S3}, and C_{S4}. This is indicative that some students performed well on their group projects, but much poorer on their individual assessment and scaled team project marks as shown through the C_{S3} and C_{S4} memberships. Their formative results are spread out between C_{F1}, C_{F2}, C_{F3}, and C_{F4}, with their strongest membership being C_{F3}. The variance of the memberships suggests that students do not perform uniformly well on the formative assessments, but rather excelling in some activities and performing less well in others. L_5 engagement patterns vary a lot, with strong memberships to C_{E3} and C_{E4} and a weak membership to C_{E1}. The strong membership to C_{E4} indicates that these students had very little online engagement to the course, but still managed to achieve a reasonable grade. The slight C_{E1} membership shows that these students spent a lot of time utilising course-learning resources, and the remaining membership to C_{E3} indicates a neglect of use of the *Help!* tool, but good engagement elsewhere.

L_4 constitutes 60 students (7%) of the class population. The lower achieving students have distinct summative feature membership split between C_{S3} and C_{S4}. This shows that students in L_4 generally performed poorly on all summative assessment, and have relative poor team performance. L_4 formative results split have a distinct split between C_{F3} and C_{F4}. The majority of membership to C_{F4} indicates that poor achievement in most formative assessments, while the membership to C_{F3} shows relative average formative scores. Engagement patterns are divided between C_{E3} and C_{E4}, with a small membership to C_{E1}. These memberships indicate that there was a lot of variance in the way L_4 sought knowledge in the course. 36 percent of students in this cluster had high levels of *Learning Pathway* engagement, with relatively low *MOOCchat* engagement and time spent viewing questions on *Casper.* These students had no *Help!* engagement. Conversely, 46 percent of students in L_4 had extremely low engagement features and did not perform well. The remaining 16 percent of L_4 failed to achieve superior grades despite having high engagement across every tool.

L_3 constitutes 21 students (2.5%) of the class population. The failing students have a clear membership to C_{S4} and a slight deviation to C_{S3}. They have no association with the higher-performing clusters, C_{S1} and C_{S2}. Strong membership to C_{S4} indicates that the student teamwork was poor, and they performed very poorly on individual assessment. L_3 exhibits strong membership to C_{F4} and slightly less to C_{F3}, with almost no association to the higher achieving clusters C_{F1} and C_{F2}. The memberships to C_{F4} poor formative scores, and C_{F3} shows average formative scores. Engagement patterns are strongly aligned to C_{E3} and C_{E4}, showing that the students spent a lot of time seeking assistance in the *Help!* and viewing questions on *Casper*. Their lack of membership to C_{E1} and C_{E2} indicates they failed to absorb course content in the

Learning Pathway, and their MOOCchat participations were insignificant.

Discussion and conclusion

The main message to be drawn from this study is that students can take several paths through ENGG1200 in order to be successful. We can also say that students receiving a grade of high distinction have good formative assessment results, their engagement is high and that they do well on individually oriented tasks. They tend to be highly engaged in tasks requiring both on campus and online presence, including tasks that require strong participation.

Perhaps the equivocal findings in the literature on the role of attendance and participation relate to a more complex pattern of interaction and engagement overall than previous analyses and research has revealed for all students. Limiting learning analytics to purely behavioural measures, such as clickstream data, without considering cognitive or affective states would be a mistake. However we also need to be mindful of creating learning analytics that are so course specific they are not predictive or useful for judging success in other contexts.

Analysing the learning pathways of students in a blended course that uses a suite of online tools and support systems for delivering a more personalised learning experience is a challenging, open research problem. In this paper, we employed a novel technique, from the fields of data mining and visualisation to investigate the variations and similarities of student's approaches to learning against those who achieved similar final course grades. Analysis using k-means clustering reveals that students do in fact, adopt very different pathways through the course, suggesting that there are multiple pathways to success in this course.

Perhaps this indicates a shift away from focusing on narrow predictive measures of success to looking at how students can achieve the same overall measure of success in forms of grade, despite having different patterns of interaction with the course and the tools provided in the course. There are several interesting directions to pursue in future work. Our first goal is to utilise the results of the paper to make updates to the course to further enhance the learning experience of the students. A longer-term plan is to release the learning dashboard that was used in this research as an open-access tool, allowing other educators to investigate the learning pathways of students in their own courses.

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Appendix 1

Table 1: High-level code for the approach used in this study

S =	selectSummative(L) # features pertaining to summative assessments in S
F =	selectFormative(L) # features pertaining to formative assessments in F
E =	selectEngagement(L) # features pertaining to student engagement in E
K_S =	elbow(S) # determine the number of clusters to be used in clustering S
C_S =	kmeans(S, K_S) # cluster S using K_S clusters
K_F =	elbow(F) # determine the number of clusters to be used in F
C_F =	kmeans(F, K_F) # cluster S using K_F clusters
K_E =	elbow(E) # determine the number of clusters to be used in E
C_E =	kmeans(E, K_E) # cluster E using K_E clusters for (i=3; i<=7; i++) analyseRQ1(L_i, C_s, C_f, C_e) # examine and analyse the behaviour and performance of learners with course-grade i (L_i) with reference to their associated clusters in C_S, C_F, and C_E

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