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Cluster Analysis of Assessment in Anatomy and Physiology for Health Science Undergraduates

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Academic content common to health science programs is often taught to a mixed group of students; however, content assessment may be consistent for each discipline. This study used a retrospective cluster analysis on such a group, first to identify high and low achieving students, and second, to determine the distribution of students within clusters based on their chosen program of study. Using a two-step cluster analysis based on five summative assessment scores for 773 undergraduate students, three distinct groups of students were identified: these are described as High Achievers, Standard Achievers, and Low Achievers. High Achievers scored higher in all five assessments compared with Standard Achievers and Low Achievers (all $P < 0.01$). Also, Standard Achievers scored higher than Low Achievers in all assessments. Membership of the High Achievers cluster comprised 15% Midwives, 20% Nurses, 10% Occupational Therapists, 11% Paramedics, 24% Physiotherapists, and 21% Standard Pathway students. This novel approach provides an opportunity for quantitative reflection on assessment in a large group of students with diverse career aspirations. It may be used to distinguish levels of achievement relative to peers within a group and potentially identify students within a program of study in need of academic assistance.

An introductory undergraduate course in Human Anatomy and Physiology is often considered a pre-requisite for further academic study in many health related professions. However, the delivery of common anatomy and physiology content to a varied student group which may contain individuals with different career aspirations can be challenging. Also, the assessment strategy used in such circumstances may focus on demonstrating the mastery of course content, but remain inflexible regarding the diverse career aspirations of the student group. Part of the role of the educator is to provide an appropriate assessment strategy which allows a student the opportunity to demonstrate knowledge and understanding of the course content; however, the development of the assessment strategy should also be sensitive to the requirements of the students. Assessment is important in helping to guide student learning as it both influences the approach to learning (Breckler, Joun, & Ngo, 2009; Marden, Ulman, Wilson, & Velan, 2013) and may confirm the achievement of a learning outcome (Marton & Säljö, 1976). Assessment can be classified as either formative or summative. Formative assessment provides students with appropriate feedback to support the achievement of a learning outcome (Rolfe & McPherson, 1995) and is intended to provide feedback in a non-threatening environment (Dobson, 2008). Formative assessment usually has no course credit assigned to it (Olson & McDonald, 2004; Peat & Franklin, 2003). In contrast, summative assessment is primarily used to grade students (for example, at the conclusion of a study period), often without providing feedback to students on their performance. Scores achieved in summative assessments are often emphasized by both educators and students, and performance in these assessments may be the decisive factor of a students' progression (Lin, Liang, & Tsai, 2012).

Classifying students according to their performance in assessment tasks is a long-standing tradition within academia: it provides a means to grade and rank students with regard to their peers, national standards, or the level to which learning outcomes have been achieved. Multiple, but common, assessment tasks with large and diverse groups of students can present considerable challenges when attempting to navigate through student performance. Therefore, in this research article, we aim to use a novel two-step cluster analysis to group students according to their performance in summative assessments, taken as part of a large introductory anatomy and physiology course by students enrolled in a variety of named health degree pathways. The clustering analysis, which is a form of data mining, identifies clusters embedded in data where a cluster is a collection of data objects that are similar to one another (Everitt, Landau, Leese, & Stahl, 2011; Kaufman & Rousseeuw, 2005; Romero, Ventura, & Garcia, 2008). Cluster analysis techniques can be applied to educational systems such as traditional education, and distant education, as well as to learning content management systems (Darcan & Badur, 2012; Romero et al., 2008). To the authors' knowledge, a cluster analysis has not been applied to summative assessment scores in a large undergraduate introductory course in anatomy and physiology, where the student group consisted of a diverse range of named degree pathways. It was hypothesized that this approach may be used to identify groups of students based on academic achievement and to provide the educators with quantitative data on the importance of each assessment in determining achievement on the course.

Methods

Setting

The anatomy and physiology course was a compulsory first-year, first semester course taken by all students enrolled on the Bachelor of Health Science (Standard Pathway) program, and by students on the Bachelor of Health Science program with the named pathways in Midwifery, Nursing, Physiotherapy, Occupational Therapy, and Paramedicine. The course was delivered as a weekly three hour lecture (recorded at the time of initial delivery and made available to all students for the remainder of the course), and a weekly two hour tutorial, over a continuous 13-week period. All lecture slides could be pre-purchased by students, and additional work sheets were used to support learning outcomes in the tutorial sessions. Two 1-hour laboratory sessions were also part of the course, these being a bone and joint dissection (bovine), and a heart and lung dissection (lamb). Students were strongly encouraged to purchase an introductory human anatomy and physiology text, and although not compulsory, attendance at both lectures and tutorials was strongly encouraged.

Each student in the course was assessed using five summative assessments: a weekly on-line multiple choice test, a mid-semester multiple choice test, and a final examination with three separate sections: (1) a multiple choice test; (2) a "matching" test, where content knowledge was examined by matching a list of possible answers to a series of images, statements and diagrams; and (3) a long answer, handwritten section. The weighting (proportion of course credit) allocated to each assessment was 10% for the on-line tests, 30% for the mid-semester test, and 60% for the final exam. Within the 60% total available for the final exam, individual sections of the final exam were allocated weightings of 30% for the multiple choice component, 10% for the matching component, and 20% for the long answer component. All information about assessment weighting, timing, and appeal processes were made available to all students at the start of the course (as hard copy documentation), and available as an on-line document throughout the course. For all assessment tasks, marking rubrics (indicating what would be expected to achieve high, medium, and low marks), indicative sample questions, and suggested revision schedules and topics were provided to all students. Also in weekly tutorials, time was allocated to revision of past exam papers (available on-line), and educators encouraged students to practice answering each of the types of assessment used in the course. For all topics covered in the course, weekly learning objectives were provided; also, it was made clear which learning objectives were to be assessed by each assessment task.

The course attracted students with a diverse range of pre-university educational experiences, including those re-entering formal education following a period of either work or unemployment. Approximately 60% of the students enrolling into the course were direct entrants from their final year at school (students aged 18 years). All students were 18 years or older, and "mature" students were those students 25 years and older. The gender balance was approximately 50:50; however, some named pathway programs (for example, midwifery) were predominantly female (>90 %). Demographics of the students in the course were not specifically collected for this study, as access to both student identity and confidential personal details were restricted in the University's data management system. Anecdotally, at this university, the physiotherapy and occupational therapy pathways attracted fewer mature students (<10%), whereas the paramedicine and midwifery pathways attracted more mature aged students (>75%). Students attracted to the nursing pathway were predominantly female with approximately 20% mature students.

Data Collection and Analysis

Data were accessed from the University's data management system (ARION), with the approval of the course co-ordinator. Throughout the analysis, de-identified, aggregated data were used, thus presenting no student privacy issues. Although this study did not require a full submission to the University Ethics Committee, appropriate advice was sought from the Faculty representative on the committee, the University Research Advisor, and the University Privacy Officer. A condition outlined by the committee and the University Privacy Officer was that only de-identified, aggregated student data could be accessed for the research analysis; therefore, no individuals could be identified by the researchers, nor could a student identify their own data from the analysis.

The two-step cluster analysis is an exploratory strategy designed to reveal natural groupings (or clusters) within the data set that otherwise would not be apparent. The two-step method has the advantages that no a priori allocation of the number of clusters is required and that the importance of each input variable for the construction of a specific cluster is identified. The method standardizes all input variables but does not allow a missing value for any input variable. Previous (unpublished) pilot work on a smaller data set (n=339) of undergraduate nursing students from an Australian university indicated the suitability of this technique for this application.

All data were analyzed using SPSS (IBM SPSS Statistics 22). Each numerical score for the five assessments was used as an input variable in the cluster analysis. All scores were considered as continuous variables. The range of marks available for each input was 0 – 314 for the online test (online), 0 – 50 for the mid-semester multiple choice test (mid sem), 0 – 50 for the multiple choice section in the final exam (Exam MC), 0 – 20 for the matching questions section in the final exam (Exam Match), and 0 – 30 for the long answer section in the final exam (Exam LA). All inputs were standardized such that no input score was allocated a higher weighting than any other, the number of clusters was determined automatically, and the distance between variables for cluster allocation was determined using the Log-likelihood method. Clusters were compared with a one-way analysis of variance and a Bonferroni post hoc test for multiple comparisons, where the mean difference was considered significant if $P < 0.03$.

Results

Data were included for 773 undergraduates enrolled in a compulsory introductory course in anatomy and physiology. Missing values were noted in 40 students (4.9%). Any student with a "missing" value for an assessment was excluded from the analysis; however, any student that scored zero in an assessment was included. The two-step cluster analysis elicited a model that was a fair to good fit based on a 0.5 silhouette measure of cohesion and separation. Also, the clusters were well defined, based on the analysis of the centroids for each input – all clusters were significantly different for all inputs. The two-step cluster analysis returned a model with 3 identified clusters, with 339 (43.9 %) students in cluster 1, 280 (36.2 %) students in cluster 2, and 154 (19.9 %) students in cluster 3. The clusters have been described as High Achievers (cluster 1), Standard Achievers (cluster 2), and Low Achievers (cluster 3). This choice of descriptive terminology is an interpretation based on the mean achievement scores for each input variable. The mean and standard deviation of each input variable for the defined clusters are shown in Table 1. Means were compared with a one-way analysis of variance, and where significant, a Bonferroni post-hoc test with adjusted alpha ($P<0.03$). All mean inputs in the High Achievers cluster were significantly higher than those in both the Standard Achievers cluster and the Low Achievers cluster. Also, all mean inputs in the Standard Achievers cluster were significantly higher than those in the Low Achievers cluster.

The spread of each input variable for each cluster is compared between clusters, and with the total group, as shown in Figure 1. For each input in Figure 1, a box denotes the median with upper and lower quartiles as the limits of the box, and imposed on this are point and whisker plots for each cluster, where the point denotes the median for that cluster and the whiskers denote the upper and lower quartiles for the cluster. In the current study, the online assessment was the least important input in determining cluster membership: this means that the input which was least likely to identify the level of achievement was the score in the online tests. This may suggest that a future delivery of the course uses the online component for formative assessment rather than summative; however, when formative assessments are optional with no course credit assigned, there may be a lack of student engagement with them (Kibble, 2007; Marton & Säljö, 1976).

The distribution of programs within each cluster was determined and is shown in Figure 2. The High Achievers cluster comprised 15% Midwives, 20% Nurses, 10% Occupational Therapy, 11% Paramedics, 24% Physiotherapy, and 21% Standard Pathway. The Standard Achievers cluster comprised 9% Midwives, 16% Nurses, 16% Occupational Therapy, 4% Paramedics, 16% Physiotherapy, and 39% Standard Pathway. The Low Achievers cluster comprised 5% Midwives, 16% Nurses, 12% Occupational Therapy, 1% Paramedics, 2% Physiotherapy, and 63% Standard Pathway.

Clusters were identified using a two-step cluster analysis of 773 first year undergraduate health science students completing a compulsory introductory course in anatomy and physiology at a large, publicly funded university. The upper pie indicates the High achievers (n=339 students), made up of 50 Midwifery, 67 Nursing, 33 Occupational Therapy, 37 Paramedicine, 82 Physiotherapy, and 70 Standard Pathway students. The middle pie indicates the Standard achievers (n=280 students), made up of 24 Midwifery, 46 Nursing, 44 Occupational Therapy, 11 Paramedicine, 45 Physiotherapy, and 110 Standard Pathway students. The lower pie indicates the Low achievers (n=154 students), made up of 8 Midwifery, 25 Nursing, 19 Occupational Therapy, 2 Paramedicine, 3 Physiotherapy, and 97 Standard Pathway students.

Discussion

This study analyzed the academic performance of a group of health science undergraduate students on an introductory course in anatomy and physiology. The majority of students (64 %) were enrolled in degree programs with named pathways leading to recognition and/or registration as a specific health professional, with the remainder (36 %) on a standard pathway. We uniquely used a two-step cluster analysis to identify 3 clusters (groupings within the data) which have been described as High Achievers, Standard Achievers, and

Table 1

Mean (SD) Input Variables for Each Cluster

Two-Step Cluster		Input variable				
		Online	Mid_Sem	Exam_MC	Exam_Match	Exam_LA
Cluster 1 High Achievers	Mean	299.8	44.4	41.8	18.7	22.3
	SD	26.1	3.6	4.6	1.7	4.6
Cluster 2 Standard Achievers	Mean	272.9	37.8	29.7	14.5	9.8
	SD	54.3	4.5	5.1	2.9	5.1
Cluster 3 Low Achievers	Mean	216.6	28.7	20.3	8.2	3.2
	SD	82.1	5.5	4.7	3.2	3.0

Note. All variables were significantly different between clusters ($p < 0.03$) using one-way ANOVA and Bonferroni post hoc comparisons.

Figure 1

Cluster comparison based on summative assessment inputs where the clusters are High Achievers (cluster 1), Standard Achievers (cluster 2), and Low Achievers (cluster 3)

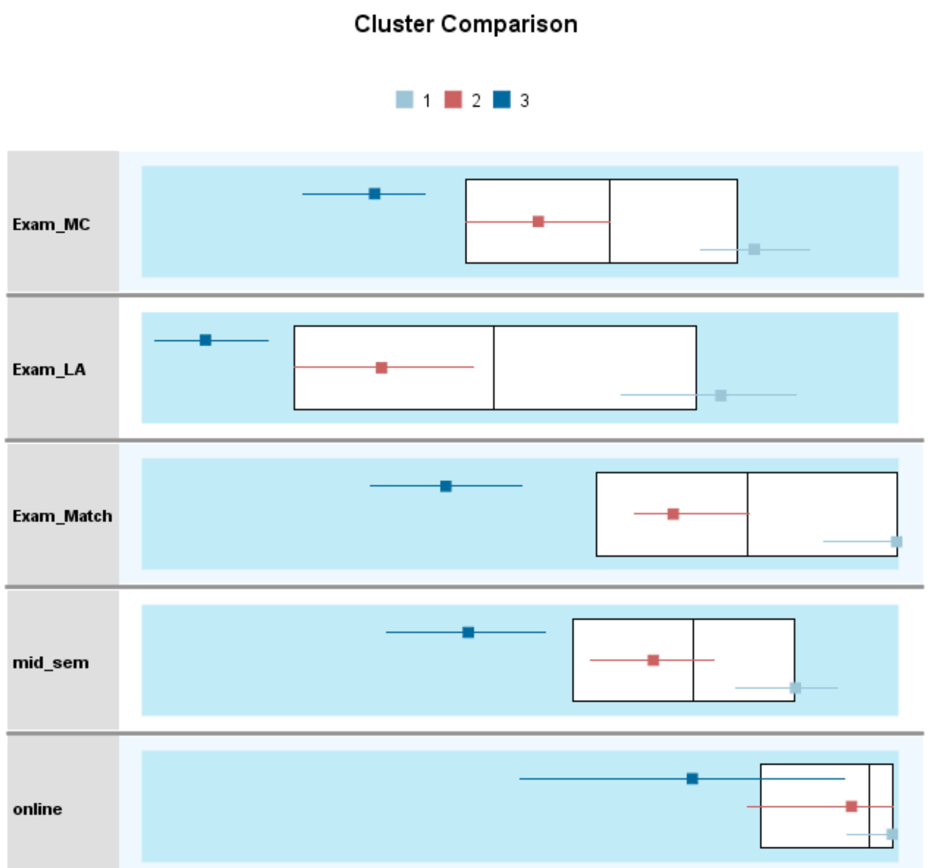
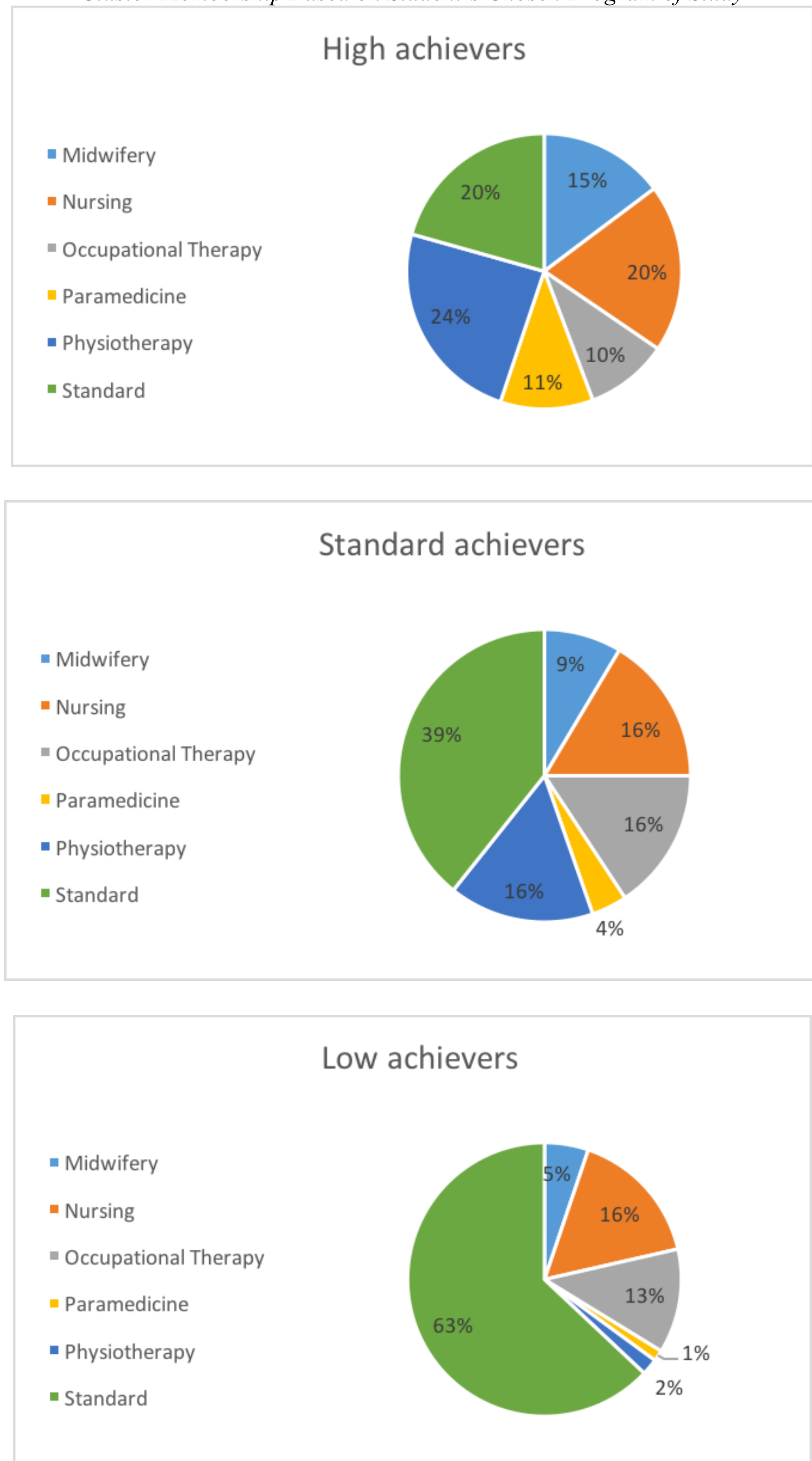


Figure 2

Cluster Membership Based on Student's Chosen Program of Study



Low Achievers. The distribution of students on each named pathway was identified within each cluster, thereby allowing academic performance to be compared between students in the same cluster and between students on the same program in different clusters.

Our analysis strategy allowed those students who were considered Low Achievers to be identified early in their undergraduate education. Based on this approach, a more strategic allocation of resources to students who may benefit from extra assistance—for example, additional tutorial opportunities, mentoring, peer assisted study support, tutor-led seminar sessions, and/or discussion groups designed to enhance learning skills—may be implemented. The cluster analysis did not take into account the final grade achieved by any student. Attainment of a pass for the physiology course necessitated a combined aggregate score of at least 50 %, and this was not a criteria for inclusion into a cluster. Therefore, it is possible that all students, including all those in the Low Achievers group, passed the course. Although a high pass rate may satisfy some requirements for future progression within the University, it may have limited use in course evaluation, planning, and the progressive evolution of the course. Thus, we suggest that the cluster analysis, as described in this study, is a more useful mechanism by which student performance in a course can be evaluated.

The cluster analysis technique has the advantage that the construction of the cluster was based on each input and that students could be compared against their peers within the same cluster. This is beneficial to educators because a cluster may show a consistent pattern of scoring either higher or lower in some inputs, thus highlighting a benefit or disadvantage to some students. This may also identify a consistent weakness in a group of students, for example, students with a particular interest in one area of content (e.g., an interest in musculoskeletal anatomy common in physiotherapy and occupational therapy students) may score well in one assessment, and poorly in another. However, the failure to grasp a particular area of content, for example neurophysiology, may indicate a poor understanding of an underlying concept (e.g., chemistry). Thus, the cluster analysis may identify groups of students who are stronger in some areas of science and weaker in others. At this University, enrollment in a named pathway (e.g., Bachelor of Health Science in Midwifery) occurred at the point of entry, in contrast to some universities which use academic performance in a common suite of courses to determine suitability for named pathways. We suggest that the cluster analysis may be a useful approach to identify high achievers, thus providing a quantitative rationale for discriminating students into appropriate courses.

The largest group in the low achieving cluster were students who were enrolled in the Bachelor of Health Science (Standard pathway). This may suggest that this program attracted less academically able students at the point of enrollment. However, the second largest group in the high achieving cluster was also the Standard pathway students, suggesting that some students in this program were equally capable of attaining success in their academic work. At this University, the named pathways within the Bachelor of Health Science have traditionally chosen students at enrollment based on their past academic performance, with entry into physiotherapy and paramedicine pathways attracting students with the highest past academic performance. Our analysis suggested that students on these named pathways continued to achieve high academic success, with only five students from these named pathways in the Low Achievers cluster.

It has been suggested that the theoretical underpinning of biological sciences in undergraduate nurse education has been borrowed from medicine (Akinsanya, 1987) where the biological sciences, including physiology, genetics, pharmacology and biochemistry, are both fundamental to nursing knowledge and an essential part of the nursing curriculum (Trnobranski, 1993). However, some aspects of the biological sciences were perceived as difficult by many student nurses (Scalise, Claesgens, Wilson, & Stacy, 2006), and although physiology was considered an essential part of nurse undergraduate education (Davis, 2010), knowledge of the sciences which underpinned undergraduate physiology was limited. Others (Jordan, 1994; Jordan & Reid, 1997) have stated that knowledge of physiology was perceived by health professionals as important, essential for questioning medical decisions and ensuring patient safety, but was limited in its undergraduate delivery. In the current study, the Low achievers cluster was populated by 25 nursing students (18.1 % of all nursing pathway students), suggesting that some undergraduate nursing students struggle with anatomy and physiology content. While this may be multifactorial, the lack of specific application of the physiology content to nursing may be a contributing factor. The delivery of compulsory anatomy and physiology content to nursing and midwifery students has presented some problems at this University, where a reluctance exists to allow students to be taught "outside" of their discipline. The cluster analysis reported in this study may provide empirical evidence on which to support (or reject) the benefit (or lack thereof) of combining students on different degree pathways in an anatomy and physiology course.

Performance in assessment continues to represent a pivotal role in students' conceptions of learning science. Teaching and learning which is test oriented may favor students who adopt a strategic learning style (Breckler et al., 2009; Dobson, 2010); however, comprehension of physiology requires students to meaningfully retain facts and competently use those facts in complicated situations (Taradi, Taradi, Radic, & Pokrajac, 2005). Therefore, a strategic approach to learning physiology which focuses on test scores may achieve only limited success. In contrast, in an inquiry instruction environment, for example, process-orientated guided inquiry (Brown, 2010; Vanags, Pammer, & Brinker, 2013), and instruction focuses more on the learning process and evaluation does not mainly rely on the students' test performance (Lin et al., 2012). A student's attitude to the material and their engagement with the course may also influence performance in assessment. For example, completing all tasks on time, attending all scheduled classes, and performing the recommended revision tasks will increase the likelihood of success in assessment. We suggest that a future cluster analysis of a similar group could include psychometric measures (e.g., cognitive and affective components of attitude) and measures of engagement (e.g., commitment and association), and assessment scores.

In this study we have demonstrated the utility of using a two-step cluster analysis on summative assessment scores from a large group of students studying a common introductory course in anatomy and physiology. The identification of a group of high achievers, standard achievers, and low achievers, and the ability to identify the population of these groups based on the named degree pathway chosen by students, represents a technique which can provide an empirical basis for curriculum development.

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