Using course level data analytics to evaluate student learning outcomes & engagement

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ABSTRACT

This paper describes a process for evaluating student learning at the course-level. Course-level data is used to inform continuous improvement of program-level assessment. The sample consists of direct and indirect measures related to 101 students enrolled in a principles of financial accounting course. Direct measures indicate that most students meet or exceed learning expectations. Students scored higher on questions related to lower levels of Bloom's taxonomy (1956). Indirect measures indicate students perceive stronger than actual performance. Students not meeting the threshold of performance, cite student engagement as the reason. As engagement is paramount to success in COVID-19 learning environments, results are relevant for informing assessment interventions.

Keywords: assessment, accounting education, course embedded assessment, learning analytics; student learning outcomes

JEL Classifications: I20; M41

Data Availability: the data is available from the authors.

INTRODUCTION

Business schools seek accreditation to document a level of acceptable quality in their degree programs. To meet accreditation standards, faculty and administrators pursue the continuous improvement of programs. In the aftermath of the COVID-19 pandemic, business education programs may find it more challenging to show improvements as traditional delivery modalities have become untenable. As online, hybrid, high-flex delivery modalities rapidly replace traditional instruction, faculty and students face a multitude of challenges to teaching, learning and assessment. Research is needed to identify program related areas in need of improvement and to measure the effectiveness of interventions.

The process used to create and evaluate assessment data artifacts has many challenges. Data validity (truthfulness), data reliability (ability to replicate), timeliness of reporting and interventions, level of granularity, faculty bias and faculty buy-in are frequent concerns cited in the literature (Garfolo et al., 2015; Kim and Helms, 2016). Improving access to a wider array of course-embedded data artifacts at the student-level of analysis would help address some of these challenges. With the use of emerging data management tools and access to more robust data sets, higher education can benefit from real-time business intelligence to drive high-impact change in student learning (Grant, 2012; Chaurasia, Kodwani, Lachhwani, and Ketkar, 2018).

This paper's contribution to the literature includes the design of extensive learning analytics. It provides a data-driven process to analyze assessment data, examines curricular difficulty as an explanatory variable, and provides insight on student engagement. An appeal is made for developing stronger technology for managing data, data visuals and assessment efforts, and for using more granular data for examining student performance results.

The remainder of the paper is organized as follows: literature review, hypothesis development, data and methodology, results, and conclusions.

LITERATURE REVIEW

The literature review includes studies that promote course-level assessment, examine direct and indirect measures of student performance, and discuss the use of improved learning analytics to support assessment, improve instruction, and evaluate student learning.

Course-level Unit of Analysis

Often assessment of student learning is documented at the end of the academic program in a capstone course (Ammons and Mills, 2005). Faculty and administrators review results and apply a 'treatment' to areas in need of improvement (closing the loop). There are multiple problems with this approach, not the least of which is learning, and the assessment of learning, are not happening in an immediately sequential manner. At the point of assessment, it is unclear whether the reason for a performance deficit is an issue of cognitive retention, instruction, curricula, assessment, or some combination of issues. Removing the cognitive retention issue requires the assessment analysis to move from the end of the program to the course-level where learning occurs.

Ammons and Mills (2005) describe several benefits of course-level assessment to program-level evaluation. Examples include reduced time to collect the assessment data, improved student motivation, and improved feedback to students and faculty. Garfolo et al.

(2015, 2016) cite similar reasons for using course-level assessments to evaluate students. They find that data collection is authentic, coming from real classroom learning experiences, and students clearly see expectations and respond in a more directed manner. The benefits of course-level assessment for evaluating program-level outcomes presents a compelling framework for efficiently structuring assessment efforts.

Direct and Indirect Measures

Assessment can include direct or indirect measures. Direct measures include papers, presentations, graded assessments, and pre-post testing (Martell, 2007). Indirect measures involve the collection of opinions as to the quality of learning and are gathered by using surveys (student, alumni, employer), interviews, and focus groups.

Direct Method Literature

Santos et al. (2014) describes an approach for classifying multiple-choice questions to three-levels of Blooms taxonomy (1956). They calculate the mean performance and standard deviation in each of the skill areas. Surprisingly, they found that students scored lowest in the knowledge areas of the taxonomy. Students were not surprised by the result and confessed to not having read the textbook carefully. They expressed that their instructors spent more time on problem-solving and calculations and less time teaching facts and concepts. Clearly, student outcomes depend in large part on instructional emphasis.

LaFleur et al. (2009) describe a process of assessment using course-level measures for a principles of marketing course. They agreed that using a standardized major field test would be easier to implement but found that the content was not well matched to the course. The data from course assessments helped guide decisions about instruction, curriculum, and assessment. For instance, they found that in one section, lower scores related to an adjunct instructor, reinforcing the need for dedicated faculty, at the core level of instruction.

Barboza and Pesek (2012) examine the scores of 173 students on the Major Field Test in Business in the senior capstone course over a three- year period. Explanatory variables include grade-point average, SAT scores, academic major, gender, and analytical and writing scores from a course-embedded assessment measure. The two course-level, embedded measures were positive and statistically significant. Their overall analysis generated several relevant recommendations, but interventions related to the course-embedded measures were easier to apply.

Indirect Method Literature

Rogers (2006) believes that indirect measures of assessment are not as powerful as direct measures. However, indirect measures supply valuable information about student learning and should be included in any well-rounded assessment program.

Price and Randall (2008) examined both perceived knowledge (through surveys) and actual knowledge (through exams) at the beginning and end of the semester. Both levels of performance increased significantly during the semester, however, students did not accurately perceive their knowledge level at either event.

Combs et al. (2008) developed a survey instrument which requires students to rate perceived importance of learning goals and their ability to meet the goals. The researchers plot the results into four quadrants: A) low importance, no competence B) high importance, no competence, C) high importance, high competence, and D) low importance, high competence. The data proved helpful in guiding decisions about what to teach and how to improve the curriculum.

Boud et al. (2013) conducted a study that tracked student performance comparing direct and indirect measures of self-assessment. Although the initial results were statistically different, continual self-assessment improved and the statistical inference between direct and indirect measures diminished over the course. The results show that student judgment of their own work improves with practice and feedback.

Moore and Mitchem (2004) conduct a study of course-embedded assessment for use in an undergraduate AIS course. They administered a pre- and post-test during the semester and found significant improvements in student performance in use of spreadsheets, database systems, and graphics, but found also that students lacked confidence in their own ability to use these skills.

Technology Literature

Although course-level assessment offers the potential for improving student learning outcomes, existing systems and processes are labor intensive, often paper-based, and driven by a 'check-the-box' mentality. Ibrahim et al. (2015) and Schahczenski and Van Dyne (2019) develop a web-based interface that eases data collection, performance evaluation and tracking of continuous improvement. Course outcomes are linked to course activities so areas in need of improvement can be easily found and analyzed and the database also serves as a data repository of historical results. This advancement in assessment data management is crucial to improve the speed, accuracy, and timeliness of data collection and analysis.

The three research streams are important to the evaluation and improvement of student learning outcomes. Yet literature related to student perceptions of learning, and reasons for under or over-performance, is limited. More research is needed to study the impact of curricular difficulty and instructional emphasis on higher-order skill development. Stronger data management tools are needed to create and facilitate the data collection and analysis in a timelier manner.

HYPOTHESIS DEVELOPMENT

The purpose of this study is to support the development of a system to evaluate student learning at the course level for the purpose of informing continuous improvement efforts. The literature suggests that both direct measures and indirect measures are useful for informing course level improvements.

Research questions include:

How do we identify areas of strength and weakness in student learning? How do the weaknesses manifest? Are they related to instruction, curriculum or assessment? Are the weaknesses related to the level of difficulty of the curriculum? Are the weaknesses related to cognitive retention or student engagement?

The following hypothesis are tested:

- Most students meet or exceed the thresholds for reaching the course learning outcomes.

- Students' actual and perceived knowledge have a strong, positive correlation.
- Students' opinions about non-performance are most often attributed to self-engagement.
- Students' perform better on questions that link to lower than to higher-levels of Bloom's taxonomy (1956).

DATA AND METHODOLOGY

Data and Sample

The sample consists of 101 students enrolled in three sections of a principles of financial accounting course. Each section was taught in person by the same professor. Course-level learning outcomes were aligned to program-level learning outcomes. For each course-level learning outcome, module-level learning outcomes were written. A set of multiple-choice questions were aligned to the module-level learning outcomes for assessing learning and assigning grades. A total of 34 learning outcomes were named and 170 exam questions were mapped to relevant outcomes.

Direct and Indirect Measures

Direct and indirect measures were used to collect assessment data. Multiple-choice exam questions were used to minimize faculty bias and interrater reliability issues that often plague assessment measures. This does not ensure that the questions are valid and reliable, but it eliminates aspects of scoring bias that exist with more subjective assessment artifacts (Kim and Helms, 2016).

Surveys were administered following each exam event. Students were asked to rate their perceptions of achievement for each learning outcome that was tested. The survey used a 4-point Likert scale (strongly agree, agree, disagree, and strongly disagree). If a student disagreed, a follow-up question was asked to learn the reason for their perception. The following choices were offered: 1) Learning outcomes(s) not communicated clearly, 2) Course activities not related to learning outcomes, 3) Result relates to student self-engagement, student commitment, student perseverance, student ability to manage information, or student ability to manage time.

Creating the Data and Performing the Analysis

Question-level data was extracted from the learning management system and imported in Excel. Each row of the database represented a question from the test. The columns in the database consisted of a module reference, question difficulty level, and a learning outcomes reference. Survey responses were added to the spreadsheet and aligned to each question based on the learning outcome. Four additional columns were added representing the percentage number of responses selected for choices in the survey.

Data for each learning outcome were summarized and displayed graphically. For the direct measures, most module-level learning outcomes included more than one test question. The question results were illustrated across the horizontal axis of the bar chart and labelled according to difficulty. The vertical axis indicated the percentage of students who selected the incorrect answer. For outcomes that included more than one question, each graph included the average percentage correct for all questions and a ranking. The ranking was based on the average percentage correct. Less than 70 percent correct is considered ***approaching***, between 70 and 84.99 percent correct is considered as ***meeting*** and 85 percent or greater correct is considered having ***exceeded*** the performance objective. For the indirect measures, pie charts were used to measure the percentage of students in each of the four categories of the survey.

Other analysis includes t-tests to compare mean exam scores to mean student perceptions, and multiple regression to determine whether question-level difficulty, student perceptions, or module-content explain mean exam scores.

Table 1 displays a six-point matrix developed to aid in the interpretation of the direct measures (means and standard deviations). The matrix helps distinguish the type of intervention that might be needed to resolve the performance level rating.

RESULTS

Direct and Indirect Measures

The results and findings for the direct and indirect assessments are shown in the following Tables and Figures.

Tables II through VII and Figures I through VI display the results on each learning objective for Modules one through six. Students met or exceeded the thresholds for most learning outcomes as measured by both direct and indirect measures. However, average performance on direct measures were consistently lower than indirect measures. Often, performance decreased as the question-level difficulty increased. Statistical results for these comparisons are detailed below.

Table VIII and Figure VII list the number of learning outcomes that were classified over the three rankings. Although students exceeded exam expectations more than they perceived, they also ranked as approaching expectations more than they perceived. T-tests to compare the mean exam scores to mean perception rankings are significant at the 5% level ($p = .011568$), but explanations for the difference are unclear. If perception affects the readiness to learn, interventions to improve student interpretations about their learning performance may improve direct measures of achievement (Combs, Gibson, Hays, Saly, and Wendt, 2008).

Table IX lists the total standard deviation, average direct measure, and average indirect measure for each module. On average, students met expectations for modules one through six for direct measures and met expectations for modules one through five for indirect measures (they exceeded expectations for module 6). Hypothesis 1, ***Most students meet or exceed the established thresholds for reaching the course learning outcomes***, cannot be rejected.

Figure VIII displays the average scores for both direct and indirect measures for each module. Indirect measures are clearly higher than direct measures for each module. The difference was largest for the first module and for modules 4 and 6 which have several approaching indicators. This finding is consistent with Price and Randall (2008) but not with Boud et al. (2013) where findings show that student perceptions improve over the course.

A multiple regression analysis was performed using percentage of incorrect responses as the dependent variable, with question level difficulty, module, and survey responses as the independent variables. There is no statistical support for indirect measures as explanatory variables of exam score variability. Further t-test results indicate a significant difference in the mean scores of direct and indirect measures and a simple linear regression provides no statistical support for the indirect measure as an explanatory variable to exam performance ($p = .2977$ and r-squared = .034). In conclusion, Hypothesis 2: ***Students' actual and perceived knowledge have a strong, positive correlation,*** is rejected.

Indirect Measure: Reason for Rating

For the indirect measure, students were asked to answer a follow-up question. The following choices were offered to those who disagreed or strongly disagreed:

1. Learning objective(s) not communicated clearly
2. Course activities not related to learning outcomes
3. Result relates to student self-engagement, student commitment, student perseverance, student ability to manage information, or student ability to manage time.

Table X displays the average perception for each module and in total. Seventy-nine percent (79%) of students select student self-engagement. About 16% of students felt that the learning outcomes had not been communicated clearly and about 5% of students felt that the course activities were not related to the learning outcomes. In conclusion, Hypothesis 3: ***Students' opinions about non-performance are most often attributed to self-engagement,*** is not rejected.

Question-Level Difficulty

Each question was rated based on two levels of difficulty. Figure IX is a scatter graph of the various achievement levels of the 34 learning outcomes and includes simple linear regression parameters. The independent variable is the question level-difficulty, and the dependent variable is the percentage of incorrect scores. The percentage of incorrect responses for level-two type questions are ~16% higher than level-one ($p = 0.00000$). Hypothesis 4: S***tudents' perform better on questions that link to lower-levels of Bloom's taxonomy (1956) than on questions that link to higher-levels of Bloom's taxonomy (1956)*** cannot be rejected.

Data Management and Using Excel Software Tools

This study used Microsoft Excel to compile, analyze, sort and display assessment data for the 170 questions and survey responses. Although Excel facilitated the creation of visuals, pivot tables, t-tests, regressions, and other descriptive statistics, the data management, data creation and analysis, required significant time to complete.

CONCLUSIONS

This paper's contribution to the literature includes the design of extensive learning analytics. It provides a data-driven process to analyze assessment data, examines curricular difficulty as an explanatory variable, and provides insight on student engagement. An appeal is made for developing stronger technology for managing data, data visuals and assessment efforts, and for using more granular data for examining student performance results.

Relevant findings and contributions include documentation of a significant difference between the mean scores of direct and indirect measures, and between questions distinguished by levels of difficulty in accordance with Bloom's taxonomy (1956). Student perceptions of non-performance are most often associated with student engagement. Tools are introduced to assist in developing appropriate interventions based on rankings and standard deviations, and statistical methods are utilized to test for significance. Closing the loop strategies include improving the course level learning objectives for the course, improving the question stems and answers on the exams, and reviewing and strengthening curriculum in areas of weakness to improve student engagement and learning performance outcomes.

This study uses exam, question-level, average scores. The ability to manage student-level data (bigdata) would improve statistical inference and allow for the inclusion of other student-level variables that have potential explanatory power such as demographics, attendance, and engagement. With the challenges that COVID-19 brings to teaching, opportunities abound for identifying new and improved methodologies for examining student learning and improving student engagement central to continuous improvement efforts and high-impact business education.

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APPENDIX: TABLES & FIGURES

TABLE I: INTERVENTIONS

Criteria:	Below average standard deviation	Above average standard deviation
Exceeds (85% and above)	IDEAL - If the outcome exceeds expectations and the standard deviation is below average, the curriculum, instruction, and assessments are aligned.	IMPROVEMENT - If the outcome exceeds expectations but the standard deviation is above the average, check question stem and answers to ensure question validity and reliability.
Meets (70% - 84.99%)	IMPROVEMENT - If the outcome meets expectations and the standard deviation is below average, consider improving the learning activities to increase overall class performance.	IMPROVEMENT - If the outcome meets expectations but the standard deviation is above average, consider improving the learning activities to increase overall class performance. Check question stem and answers to ensure question validity and reliability.
Approaching (less than 70%)	IMPROVEMENT - If the outcome is approaching expectations and the standard deviation is below average, revise learning activities to increase overall class performance.	IMPROVEMENT - If the outcome is approaching expectations and the standard deviation is above average, revise learning activities. Check question stem and answers to ensure validity and reliability.

TABLE II: MODULE 1, DIRECT AND INDIRECT MEASURES

	DIRECT-MEASURES				INDIRECT-MEASURES	
Learning Outcome	Weighted-average,%	Ranking	# of MCQ (difficulty)	SD	Weighted-average,%	Ranking
LO 1.1	91.4	Exceeds	1 level one	N/A	87.2	Exceeds
LO 1.2	80.0	Meets	4 level one 1 level two	5.0	86.4	Exceeds
LO 1.3	85.0	Exceeds	3 level one 1 level two	11.0	78.5	Meets
LO 1.4	74.0	Meets	3 level one 4 level two	19.0	87.8	Exceeds
LO 1.5	70.0	Meets	2 level one 6 level two	21	82.2	Meets
MODULE 1	76.4 average	Meets	25 questions	16.9 average	84.4 average	Meets

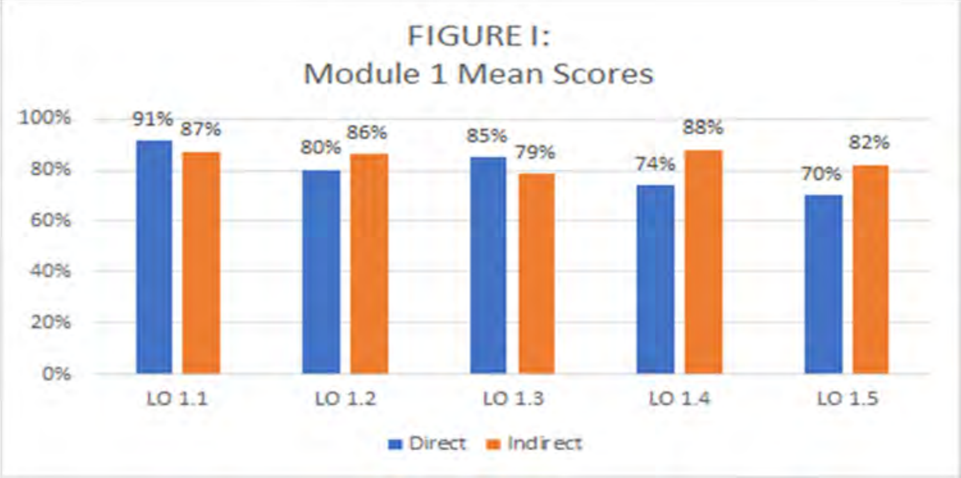

TABLE III: MODULE 2, DIRECT AND INDIRECT MEASURES						
	DIRECT-MEASURES				INDIRECT-MEASURES	
Learning Outcome	Weighted-average,%	Ranking	# of MCQ (difficulty)	SD	Weighted-average,%	Ranking
LO 2.1	86.0	Exceeds	14 level one 3 level two	13	83.3	Meets
LO 2.2	61.5	Approaching	1 level one	N/A	82.1	Meets
LO 2.3	81.8	Meets	1 level one	N/A	84.4	Meets
LO 2.4	67.0	Approaching	5 level two	19.0	83.1	Meets
MODULE 2	80.8 average	Meets	24 questions	15.6 average	83.2 average	Meets

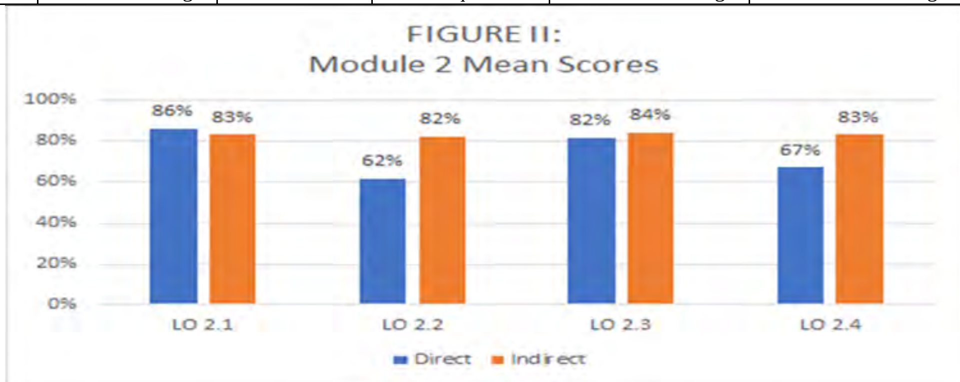

TABLE IV: MODULE 3, DIRECT AND INDIRECT MEASURES						
	DIRECT-MEASURES				INDIRECT-MEASURES	
Learning Outcome	Weighted-average,%	Ranking	# of MCQ (difficulty)	SD	Weighted-average, %	Ranking
LO 3.1	92.0	Exceeds	3 level one	7.0	80.7	Meets
LO 3.2	70	Meets	2 level one 1 level two	10.0	81.0	Meets
LO 3.3	88	Exceeds	2 level one	12.0	85.2	Meets
LO 3.4	86	Exceeds	2 level one	14.0	81.4	Meets
LO 3.5	62	Approaching	2 level one 1 level two	8.0	80.3	Meets
LO 3.6	82	Meets	3 level one 1 level two	13.0	75.8	Meets
LO 3.7	86	Exceeds	2 level one 1 level two	5.0	80.0	Meets
LO 3.8	65	Approaching	3 level one 3 level two	21.0	76.5	Meets
LO 3.9	79	Meets	2 level one 1 level two	5.0	81.0	Meets
MODULE 3	77 average	Meets	29 questions	15.4 average	80.2 average	Meets

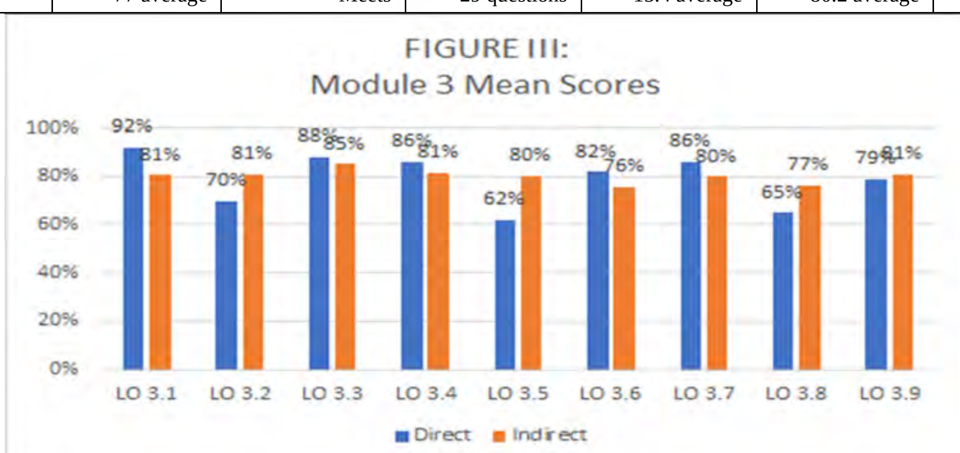

TABLE V: MODULE 4, DIRECT AND INDIRECT MEASURES						
	DIRECT-MEASURES				INDIRECT-MEASURES	
Learning Outcome	Weighted-average,%	Ranking	# of MCQ (difficulty)	SD	Weighted-average,%	Ranking
LO 4.1	63	Approaching	1 level one 1 level two	35.0	78.7	Meets
LO 4.2	81	Meets	1 level one 1 level two	14.0	84.2	Meets
LO 4.3	74	Meets	3 level one 1 level two	11.0	81.3	Meets
LO 4.4	67	Approaching	3 level one 1 level two	9.0	81.8	Meets
LO 4.5	79	Meets	4 level one 3 level two	14.0	81.1	Meets
LO 4.6	96.2	Exceeds	1 level one	N/A	80.3	Meets
LO 4.7	66	Approaching	3 level one 3 level two	23.0	82.1	Meets
LO 4.8	79	Meets	3 level one 2 level two	9.0	80.3	Meets
MODULE 4	73.9 average	Meets	31 questions	16.3	81.2 average	Meets

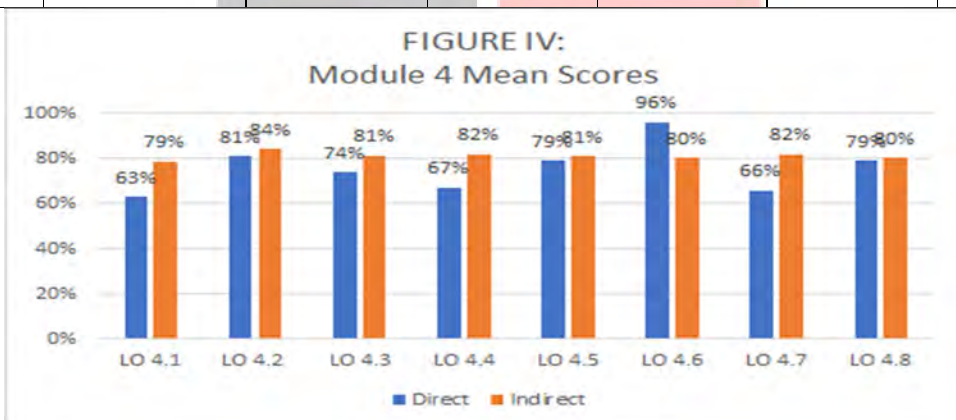

TABLE VI: MODULE 5, DIRECT AND INDIRECT MEASURES						
	DIRECT-MEASURES				INDIRECT-MEASURES	
Learning Outcome	Weighted-average,%	Ranking	# of MCQ (difficulty)	SD	Weighted-average,%	Ranking
LO 5.1	89	Exceeds	5 level one 3 level two	9.0	88.6	Exceeds
LO 5.2	75	Meets	8 level one 2 level two	27.0	86.4	Exceeds
LO 5.3	79	Meets	1 level one 2 level two	15.0	84.1	Meets
LO 5.4	96	Exceeds	3 level one	2.0	84.1	Meets
MODULE 5	82.8 average	Meets	24 questions	19.9 average	85.8 average	Exceeds

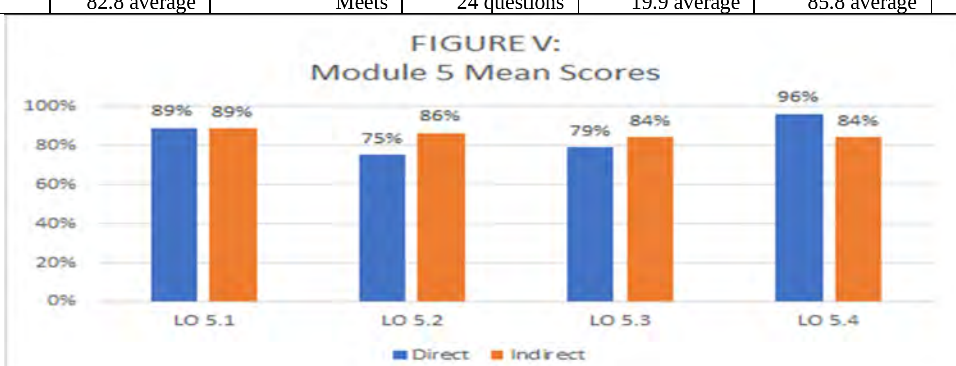

TABLE VII: MODULE 6, DIRECT AND INDIRECT MEASURES						
	DIRECT-MEASURES				INDIRECT-MEASURES	
Learning Outcome	Weighted-average,%	Ranking	# of MCQ (difficulty)	SD	Weighted-average,%	Ranking
LO 6.1	79	Meets	15 level one 8 level two	15.0	86.2	Exceeds
LO 6.2	67	Approaching	3 level one	17.0	84.9	Meets
LO 6.3	83	Meets	3 level one 2 level two	10.0	83.9	Meets
LO 6.4	74	Meets	2 level one 3 level two	17.0	88.0	Exceeds
MODULE 6	77.9	Meets	36 questions	14.5 average	85.8	Exceeds

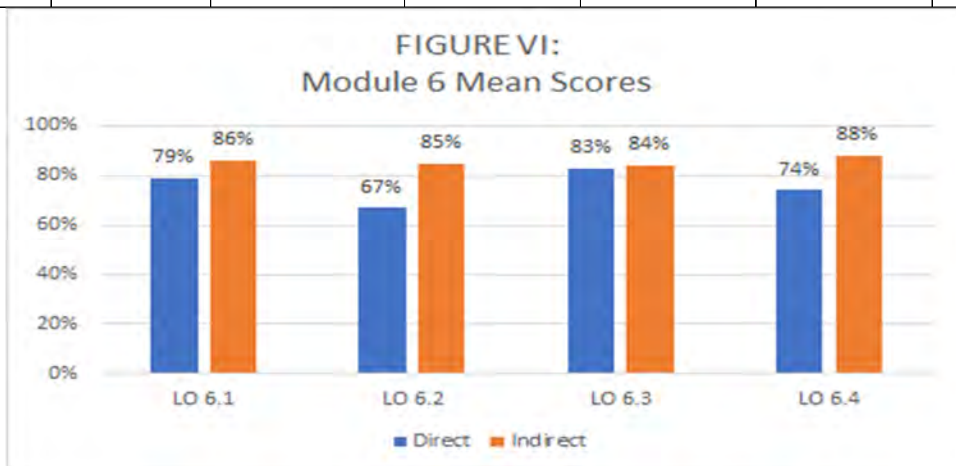

TABLE VIII: DIRECT AND INDIRECT RANKINGS		
Ranking	Direct-Measure # of LO	Indirect-Measure # of LO
Total # Exceeds	10	7
Total # Meets	16	27
Total # Approaching	8	0
Total Learning Outcomes	34	34

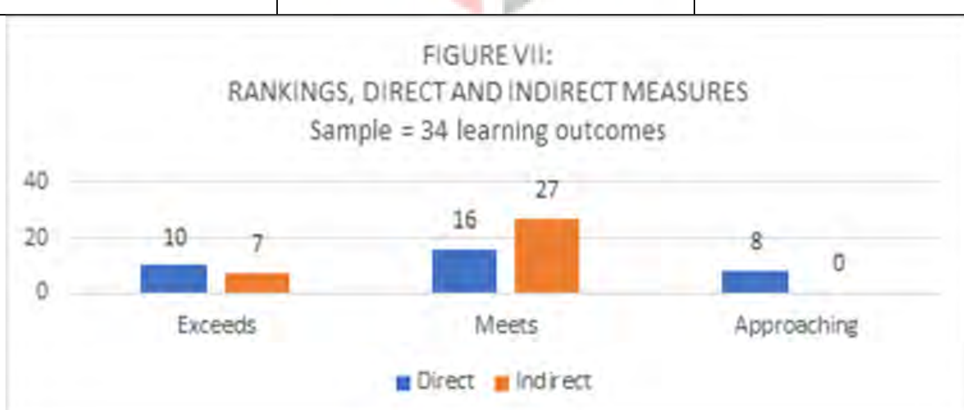

TABLE IX: MODULE AVERAGES				
MODULE	Average Standard Deviation	Average Direct-Measure	Average Indirect-Measure	Difference
M1	16.9%	76.4%	84.4%	8%
M2	15.6%	80.8%	83.2%	3%
M3	15.4%	77.0%	80.2%	3.2%
M4	16.3%	73.9%	81.2%	7.3%
M5	19.9%	82.8%	85.8%	3%
M6	14.5%	77.9%	85.8%	7.9%

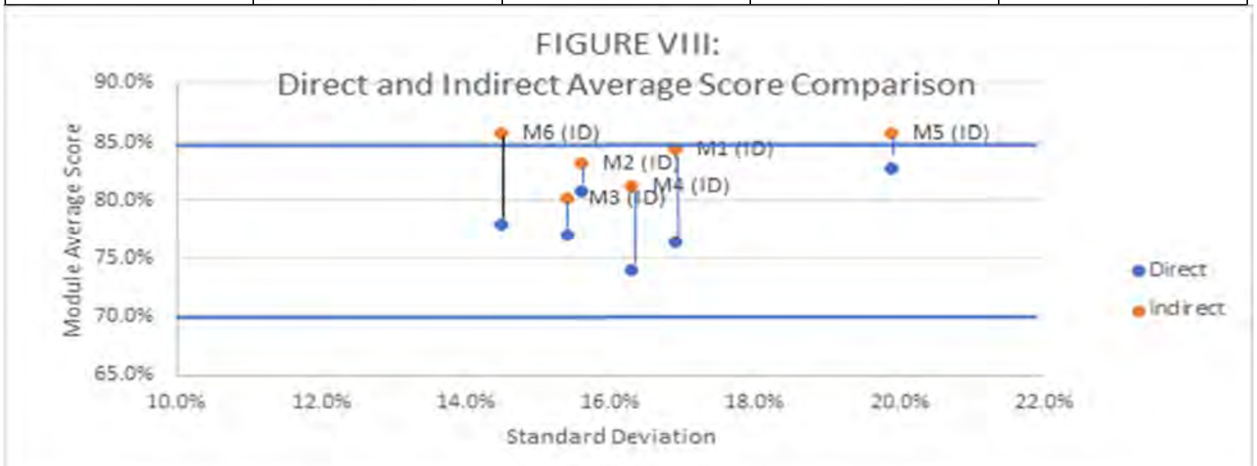

TABLE X: STUDENT PERCEIVED OUTCOME			
Module	Learning outcomes(s) not communicated clearly	Course activities not related to learning outcomes	Result relates to student self-engagement
1	10%	7%	83%
2	9%	0%	81%
3	17%	6%	77%
4	3%	0%	97%
5	23%	12%	65%
6	32%	5%	63%
Average	***16%***	***5%***	***79%***