DEMONSTRATING APPLICATIONS FOR LEARNING ANALYTICS FOR PROGRAM REVIEW

Christine Armatas and Christine F Spratt
The Hong Kong Polytechnic University
Hong Kong

Abstract

The Program Review Tool (PRT) has been developed to conduct program-level learning analytics. Examples of review outputs using the tool illustrate its value, showing how the PRT allows users to conduct analyses that provide insights for improving the curriculum and for supporting students during their studies. PRT analyses address questions about program progression and retention, factors influencing academic outcomes and how to improve the curriculum and subjects. With the PRT, users can conduct a standard review or explore program data themselves, making it a powerful yet flexible tool for enhancing program quality.

Learning Analytics Applications for Program Review

Learning analytics (LA) involves analysing data about learners to help improve learning outcomes. In this paper, a tool to support conducting data-driven program[1] review is discussed. Using this tool, the Program Review Tool (PRT), data about students' performance across all subjects in their program, from commencement to graduation, can be analysed. The PRT is designed to provide an assessment of the program as a whole and results can be used to inform what changes should be made to the program to improve the learning outcomes for students or improve the learning design or delivery. Developed as a Microsoft Excel add-in, the tool is easy to use, providing a high level of automation to the analyses while still giving users flexibility to explore the data. A standard set of review questions are addressed by analyses performed automatically using the PRT. These standard review questions and associated analyses address progress and retention rates for the program, the effect on academic performance of students' entry characteristics, what factors impact students' academic outcomes and which subjects require review or revision. Results from reviews are presented in this paper to illustrate the effectiveness of both the methodology and the tool for providing insights about the program and relationships between subjects, as well as providing information on how to support students to be academically successful. This work demonstrates the usefulness of analysing data about learners accumulated across their studies, and supports the application of LA not just to subjects, but to programs too.

Applications for Learning Analytics

LA is "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs." (Siemens, 2013, p. 1382). Research on LA applications includes studies on institutional performance metrics, e.g., attrition and progression (Arnold & Pistilli, 2012), retention (de Freitas et al., 2015), predictors of academic performance (Gašević, Dawson, Rogers & Gasevic, 2016; Dede, Ho & Mitros, 2016), and analysis of datasets from learning management systems as proxies for student engagement (Gibson & de Frietas, 2016). LA techniques can also be applied to understand the causes of at-risk learning behaviors and for assessing institutional performance (Greller & Drachsler, 2012).

LA for Program Review

While subject and institution level applications for LA have been identified and studied, LA applied to programs is relatively under-explored. However, recently Armatas and Spratt (2019) described applications for LA for curriculum review of programs that include measuring the overall difficulty of a program, examining the relationship between subject difficulty and students' satisfaction with the teaching in the subject and comparison between student cohorts on measures of academic achievement. They note that the specialist skills that some LA techniques require may make it difficult for many academics to conduct program review using an LA approach. To address this challenge, we have developed the PRT, which can be used as part of a model specifically developed to conduct program review using LA. The model has four stages (Prepare, Map, Analyse and Implement; P-MAI) and is discussed next.

The P-MAI Model

In the first phase of the P-MAI model, *Prepare*, review questions, together with what data are available and what data need to be collected or obtained (and from where), are identified. The second phase, *Map,* is where data are linked to review questions and possible analysis strategies are identified. For each review question, there may be multiple data types or sources, multiple analysis strategies or both, so decisions need to be made about what analyses to conduct in the next phase. Examples of this mapping are shown in Table 1. Analysis of the data to address review questions is conducted in the third phase, *Analyse,* and the results interpreted and reported. The results are used to develop an action plan for the final stage, *Implement*, which includes a Program Diagnostic Report that details the findings from the review. This report includes answers to the review questions based on the analyses conducted in the previous phase, with recommendations for action, learning advice for students and advice for academic advisors.

Table 1
Examples of mapping of program review questions to analysis strategies

Program Review Questions	Possible Analysis Strategies
1. Are there issues with progression or retention across the program related to specific subjects or students?	• number of students graduated within the normal study period, graduated late or not at all • Identification of subjects with high fail rates • Identification of students with lower than expected performance or progression
2. What is the relationship between subject difficulty and student satisfaction?	• Correlational analysis and visualization (scatterplot)
3. What predicts students' academic performance in the program under review?	• Testing prediction models based on students' grades and overall academic performance (e.g., entry characteristics or subject grades).

Programme Review Tool

The PRT has been designed to support the P-MAI model as a tool to conduct complex analyses for program review without the need for specialized data analysis expertise. In this paper the focus is on the third phase of P-MAI, where a standard set of analyses are conducted using the PRT to address review questions in a structured fashion, with the user able to explore the data to address other questions that may arise after the standard set of review questions are addressed.

How the PRT Works

The PRT is designed to analyse the full academic records for a cohort, which is defined as a group of students who commenced study in a program in the same academic year and who would usually graduate together. Figure 1 shows the work flow for the PRT, which starts with importing the data set containing all the academic records for each student enrolled in that cohort, with the minimum information required being students' entry characteristics, what subjects they took, the semester in which they took the subject and the grade they received for each subject.

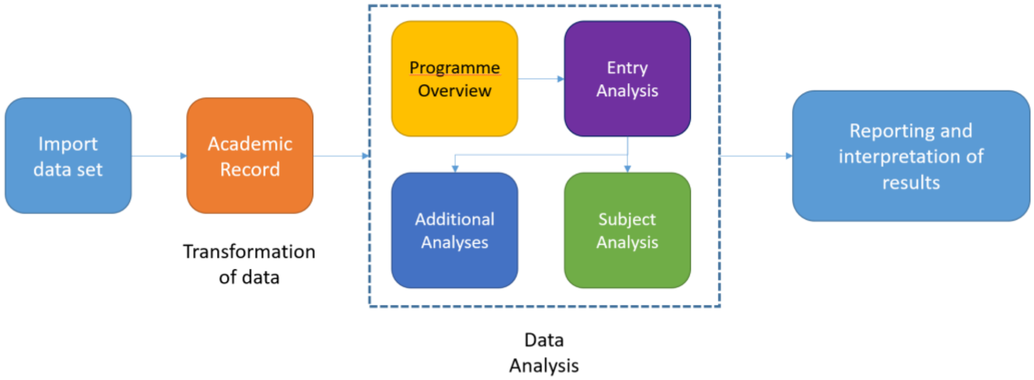


Figure 1. Workflow for the Program Review Tool.

At our University, students' academic records are provided in an Excel spreadsheet which has multiple rows for each student – one row for each subject they took during the program. Before importing these data into the PRT, the user needs to name the worksheet with the student information as "*Data*" and create another worksheet called "*Program Overview*" and provide information about what subjects are core (i.e., all students studying the program need to take these subjects), and the credit point value and duration (i.e., one or two semesters) for each core subject. The user then opens the PRT and a new menu item called "PRT" is added to the menu bar in the Excel file as shown in Figure 2.

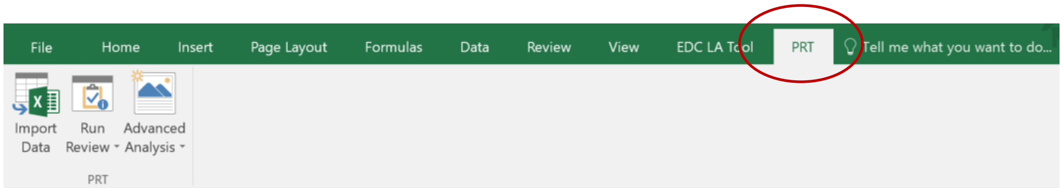


Figure 2. The *PRT* button is added to the menu bar when the tool is opened.

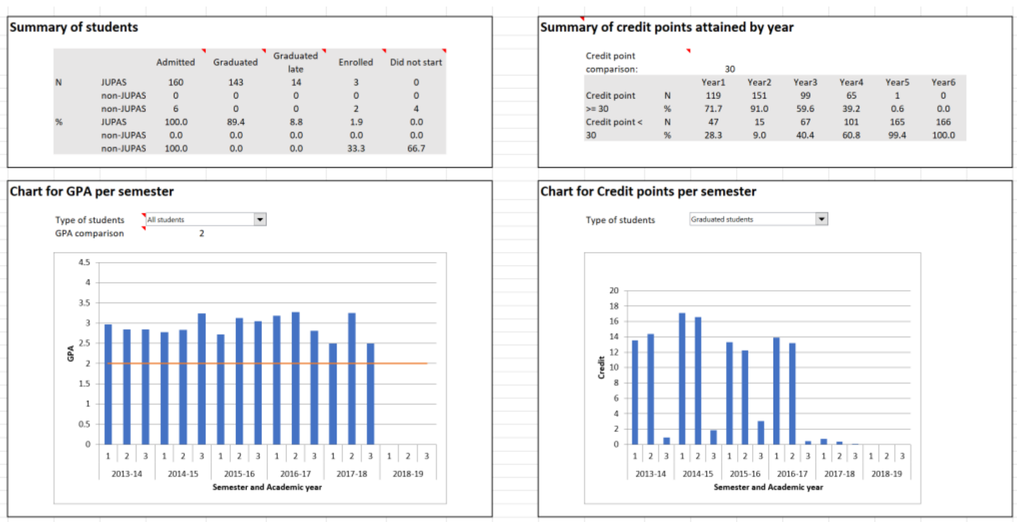
Clicking on this new button brings up three sub-menus: "*Import Data*", "*Run Review*" and "*Advanced Analysis*". The first step for any review is to import the data by clicking on the "*Import Data*" button. This brings up a window prompting the user to select the data for analysis by browsing to the file location, selecting the file and clicking OK. The data are then transformed and imported into the tool for further analysis. Transformation of the data is needed because the format of the data extracted from the University's student record system is not suitable for analysis - each student needs to have only one record (in this case a row in the Excel file) with the values for each variable recorded in columns. However, the student record extract has multiple rows for each student. Therefore, the workflow for the PRT involves importing the data in the original, multiple-row format and then transforming the data to produce an academic record where the data for a student appear in only one row in the file. After importing the data, a worksheet is produced in the Excel file called "*Academic Record*". This is a record of all data from the original data file that can be exported and used in other applications such as IBM SPSS Statistics[2] to conduct additional analysis not supported by the PRT. Once the academic record worksheet has been created, the user can then conduct analyses on the student data to address review questions such as the ones described in Table 1. Clicking on the *"Run Review"* button steps the user through a series of analyses mapped to review questions. How this process works and the outputs created using the PRT are described next, using actual program reviews.

Review Examples

Sample output from analysis of anonymized program data using the PRT for program review is provided next. These examples illustrate outputs from the tool and how this information can be used to address program review questions.

Overview of the Program

Clicking on the "*Run Review"* menu button generates an *Overview* worksheet with two tables and two charts. Figure 3 shows a screenshot of this information for a program review. The tables give information about the graduation status of students in the cohort and information about entry method[3], progression and retention. The graphs provide information about the average semester Grade Point Average (GPA[4]) and the average credit-points per semester. The user can control what information is displayed in the output for this worksheet. For example, the credit point threshold per semester can be adjusted to reflect the number of credit points students are expected to take each semester to graduate within the normal study period. A drop-down menu on the two charts allows the user to select which students (all students admitted to the program, those who graduated within the normal study period, those who graduate beyond the normal study period and those still enrolled) to display information about.



Summary of students

		Admitted	Graduated	Graduated late	Enrolled	Did not start
N	JUPAS	160	143	14	3	0
	non-JUPAS	0	0	0	0	0
	non-JUPAS	6	0	0	2	4
%	JUPAS	100.0	89.4	8.8	1.9	0.0
	non-JUPAS	0.0	0.0	0.0	0.0	0.0
	non-JUPAS	100.0	0.0	0.0	33.3	66.7

Summary of credit points attained by year

Credit point comparison: 30

		Year1	Year2	Year3	Year4	Year5	Year6
Credit point >= 30	N	119	151	99	65	1	0
	%	71.7	91.0	59.6	39.2	0.6	0.0
Credit point < 30	N	47	15	67	101	165	166
	%	28.3	9.0	40.4	60.8	99.4	100.0

Figure 3. Sample output for the Overview worksheet.

Entry Analysis

Two worksheets are produced for the next analysis, which relate to students' entry characteristics – specifically their grades on the Hong Kong Diploma of Secondary Education (HKDSE). The first worksheet, called *Entry Analysis*, lists the subjects that individual students have taken for their HKDSE and the marks they received for each subject. This list can be used to see what subject combinations students admitted to the program take for their HKDSE and to conduct further analysis to look for patterns in subjects that students take and the relationship with the GPA they graduate with (Award GPA). The user can choose which subjects to include in the entry analysis via a dialogue window that opens when the *"Run Analysis"* button is clicked. The second worksheet has a table of descriptive statistics and a bubble scatter chart based on this table. Figure 4 shows a screenshot of this output for a program, where the user has included all subjects that students admitted to the program took for their HKDSE. In Figure 4, the large bubble size indicates a large proportion of students took Business Studies, Economics and Combined Science for their HKDSE, in addition to the required entry subjects of English, Chinese, Liberal Studies and Mathematics. There appears to be little relationship between Award GPA and grades for the HKDSE subjects as shown by the flatness of the bubbles in the chart. The exception to this is the small number of students who took Chinese Literature in HKDSE who got a relatively low score for this subject but achieved a relatively higher Award GPA on graduation.

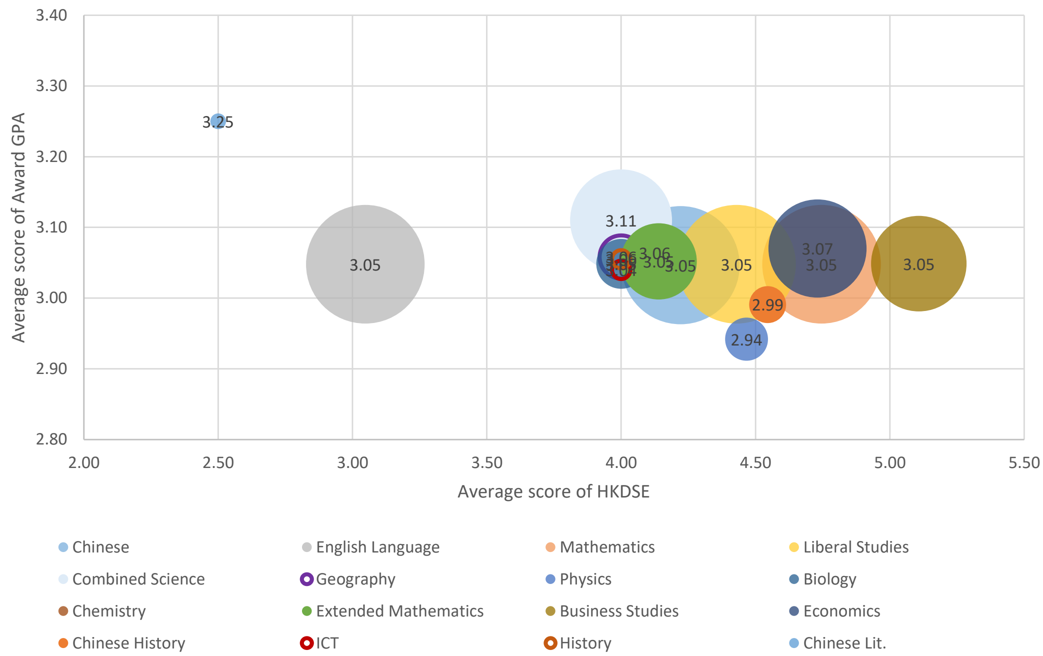


Figure 4. Output for analysis of students' entry characteristics. In the diagram, the size of the subject bubble indicates the proportion of students who took the subject, with the larger the bubble, the more students who took the subject.

The two worksheets produced for analysis of entry scores provide visualizations of subjects taken by students at HKDSE, the grades they received for them and what relationship this has with their academic performance as measured by Award GPA. The information about students' entry characteristics can also be used in advanced analyses the user may wish to conduct.

Subject Analysis

Results of subject analysis are displayed next. The first output is a series of spark charts of grade distributions for all core subjects. A sample screenshot of this output is shown in Figure 5. Displaying the grade distributions together allows visual identification of subjects that are too hard (e.g., ABC457, CDE123 and FGH124), ones that are too easy (e.g., ABC123, ABC223, FGH123) and ones that have too few grade categories (e.g., LMN345 and LMN346). This information informs decisions on which subjects should be reviewed or revised. The second output lists all subjects that one or more students in the program failed. This provides information about subjects that students may find challenging and can also be used to identify students who fail multiple subjects.

Subject	Student count	Grade Distribution A+ A B+ B C+ C D+ D F	A+	A	B+	B	C+	C	D+	D	F
			Individual Grade Counts								
ABC123	138		4	24	45	42	18	5	0	0	0
ABC223	141		7	20	37	43	25	6	2	1	0
ABC224	162		2	11	33	57	36	19	2	0	2
ABC225	162		0	3	59	50	36	13	0	0	1
ABC226	162		5	19	38	49	25	16	9	0	1
ABC345	161		6	15	24	52	34	25	4	0	1
ABC346	160		11	14	28	49	27	23	6	2	0
ABC347	160		3	13	28	24	41	40	11	0	0
ABC348	160		2	13	33	55	27	24	4	1	1
ABC349	160		4	20	42	47	27	14	6	0	0
ABC350	160		8	23	46	52	19	7	4	0	1
ABC351	160		0	23	53	58	16	8	2	0	0
ABC456	159		11	25	41	41	20	12	7	2	0
ABC457	160		1	4	24	33	52	33	12	0	1
ABC458	160		8	33	38	42	25	7	6	0	0
ABC459	158		0	16	75	57	9	1	0	0	0
ABC460	159		3	30	49	65	7	1	4	0	0
CDE123	102		6	7	9	26	18	21	10	4	1
CDE124	145		6	14	36	44	26	14	3	1	1
FGH123	137		2	40	37	32	15	6	3	2	0
FGH124	137		3	9	12	36	47	26	2	2	0
IJK345	160		0	3	35	74	37	3	2	0	0
LMN345	161		0	0	23	95	42	1	0	0	0
LMN346	160		0	4	53	87	16	0	0	0	0

Figure 5. Distribution of grades for core subjects in the program.

The third output is a scatterplot showing the relationship between subject difficulty (as measured by average grade for the subject) and student satisfaction with the subject measured by the end of semester Student Feedback Questionnaire (SFQ) – a screenshot of sample output is shown in Figure 6. This visualization is useful as it shows which subjects are difficult and students are dissatisfied with (subjects that fall in the lower left quadrant of Figure 6) and those that are easy but students are still dissatisfied with (subjects in the lower right of Figure 6).

Scatter Plot of Score Grade and SFQ Score

Subject Code	Average Grade	SFQ Score
ABC123	3.282442748	4.074813
ABC223	3.186567164	4.095632
ABC224	2.915625	4.224758
ABC225	2.99068323	4.290648
ABC226	3.075163399	3.430837
ABC345	2.923566879	4.214085
ABC346	2.99025974	4.271669
ABC347	2.795302013	4.356998
ABC348	2.929487179	4.333046
ABC349	3.126760563	4.035357
ABC350	3.222972973	4.540669
ABC351	3.212025316	4.239597
ABC456	3.207482993	3.69682
ABC457	2.693877551	4
ABC458	3.287234043	4.481828
ABC459	3.340277778	3.850825
ABC460	3.341935484	3.5
CDE123	2.738636364	4.225559
CDE124	3.042253521	4.321329
FGH123	3.329545455	4.188333
FGH124	2.737037037	4.484848
IJK345	2.993421053	3.585953
LMN345	2.934375	4.112903
LMN346	3.140625	4.028388
FAC123	2.920634921	4.4
OPQ234	3.285714286	4.239597
RST123	2.870860927	3.69682
RST234	3.122137405	3.1
RST235	3.146496815	4.481828
RST236	3.146153846	3.850825
RST456	3.165467626	3.1

Table of descriptive statistics

Subject Level	Count	Mean	Standard Deviation	Maximum	Minimum	Mode
Level 1	4466	3.068406	0.598777	4	0	3
Level 2	905	2.998343	0.629517	4	0	3
Level 3	1152	3.10026	0.594041	4	0	3
Level 4	1536	3.026367	0.57368	4	0	3
Overall	873	3.172967	0.599486	4	0	3.5

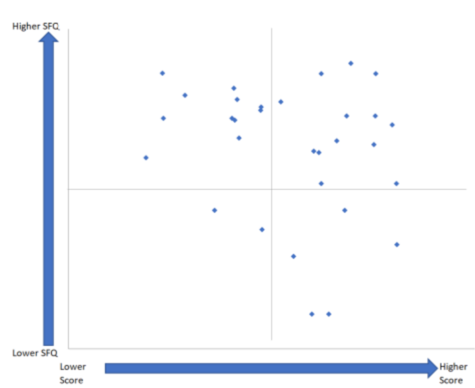


Figure 6. Summary statistics and scatterplot of the relationship between average subject grade and average subject satisfaction score (SFQ).

The output shown in the worksheets generated for *Subject Analysis* can help to address questions about which subjects students find difficult (e.g., the ones with high fail rates or low average grade), which subjects are too easy or difficult (e.g., the grade distributions are skewed to one or other end of the grading scale) and which subjects students are not satisfied with (e.g., have low average satisfaction scores on the SFQ). For those subjects identified from the spark charts of grade distribution, review of assessment practices and materials is required –a narrow range or skewed grade distributions can be addressed by examining the criteria for each grade level and ensuring that markers are applying the criteria consistently. In regard to subject satisfaction, students can be dissatisfied with a subject because it is too hard or too easy, but understanding why students feel this way and what to do about it requires further investigation.

Advanced Analyses

After the standard set of analyses have been run, the user can elect to conduct more advanced analyses. For example, under the *"Advanced Analysis"* menu, the PRT has a sub-menu item called "*Prediction*" which can be used to test models to address review questions of interest. A screenshot of the output from a model predicting Award GPA from HKDSE scores, grade in Freshman Seminar, GPA at the end of Year 1 and grade in Capstone project is shown in Figure 7. As shown in the figure, for this program, cumulative GPA at the end of Year 1 and grade in Capstone project (a major final year project) are significant predictors of Award GPA, while scores on the HKDSE and grade for Freshman Seminar (taken in first year) are not. Together, scores for these two variables account for 77.5% of the variance in Award GPA, which makes them strong predictors of this variable.

Prediction analysis results

Dependent Variable (i.e., what you are predicting) =	Award GPA
Variance in students' performance explained by these factors (R-square) =	0.775
Number of students included in the analysis =	157

Factors affecting dependent variable	Unstandardised Beta (B)	Standardised Beta (beta)	Significant Factors	Importance (Rank)
Score on HKDSE	-0.034	-0.048		
Grade in Freshman Seminar	-0.003	-0.01		
Cummulative GPA at the end of Year 1	0.524	0.699	Significant	1
Capstone Project Grade	0.114	0.385	Significant	2

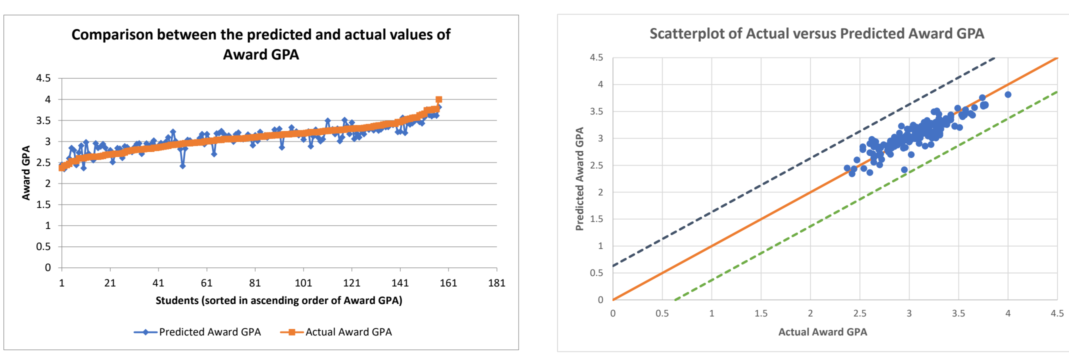


Figure 7. Example of results of regression analysis conducted using the PRT.

In addition to indicating which variables are and are not significant predictors of Award GPA, the two diagrams included with the output can be used to assess the adequacy of the model. The plot on the left of the actual Award GPA value against that predicted using the variables in the model shows good correspondence between the two, indicating this set of variables is a good predictor. This is confirmed in the diagram on the right of Figure 7 where all the points fall within the two boundary lines and fall on or near the reference line. Users are provided with visualisations such as this to help interpret the analysis results, which in this case indicate that while HKDSE score and grade on Freshman Seminar are not predictive of overall academic performance as measured by Award GPA, GPA at the end of Year 1 and Capstone Project grade are. This also highlights the importance of supporting students to be successful in first year to provide them with a foundation for future academic success.

Discussion

There are other analyses and outputs produced as part of the standard review which are not reported here due to space limitations. However, the examples provided illustrate in principle how the results from these analyses can be used to address review questions identified in the *Prepare* phase of the P-MAI. The PRT development is now at the stage where a full set of analyses can be conducted using the tool which address a predefined set of review questions, which have been developed in consultation with program leaders. To conduct a review using the PRT, the minimum information required is information about students' entry characteristics, study patterns and subject grades. Work is underway to help users turn the results into actions for improvement. Strategies to achieve this include development of resources such as videos and case-studies in collaboration with users who have conducted reviews using the P-MAI approach and the PRT.

Ultimately the usefulness of this approach will depend on whether results can be translated into actions that improve student learning. In its current format, the P-MAI approach evaluates a program based on the performance of a cohort who have already graduated. Therefore, any changes made to improve the program will happen too late to help those students. However, by understanding the factors that impact on the success of the students who have already graduated, it is possible to better support students currently enrolled in the program. The PRT makes it easier to conduct regular, data-driven program review, making it an important tool for program evaluation and quality enhancement.

References

Armatas, C. & Spratt, C.F. (2019). Applying learning analytics to program curriculum review, *The International Journal of Information and Learning Technology*, doi: 10.1108/IJILT-11-2018-0133

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. In S Buckingham Shum, D Gasevic & R. Ferguson (Eds.), *Proceedings of the 2nd International Conference on Learning*

Analytics and Knowledge (pp. 267-270). New York, NY, USA: ACM. doi: 10.1145/2330601.2330666

de Freitas, S., Gibson, D., Du Plessis, C., Halloran, P., Williams, E., Ambrose, M., & Arnab, S. (2015). Foundations of dynamic learning analytics: Using university student data to increase retention. *British Journal of Educational Technology, 46*(6), 1175-1188. doi:10.1111/bjet.12212

Dede, C., Ho, A., & Mitros, P. (2016, August). *Big data analysis in higher education: Promises and pitfalls*. Retrieved from https://er.educause.edu/articles/2016/8/big-data-analysis-in-higher-education-promises-and-pitfalls

Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *Internet and Higher Education, 28*, 68-84. doi: 10.1016/j.iheduc.2015.10.002

Gibson, D., & de Freitas, S. (2016). Exploratory Analysis in Learning Analytics. *Technology, Knowledge and Learning, 21*(1), 5-19. doi:10.1007/s10758-015-9249-5

Greller, W., & Drachsler, H. (2012). Translating Learning into Numbers: a generic framework for Learning Analytics. *Educational Technology & Society, 15*(3), 42-57. Retrieved from http://www.jstor.org/stable/jeductechsoci.15.3.42.

Siemens, G. (2013). Learning Analytics: The Emergence of a Discipline. *American Behavioral Scientist, 57*(10), 1380-1400. doi:10.1177/0002764213498851

Notes

1. A “program” is an award or degree, consisting of core and elective requirements a student must complete to be awarded the degree. At our university, most undergraduate degrees have a four year duration.
2. IBM SPSS Statistics https://www.ibm.com/products/spss-statistics
3. Hong Kong Universities have two entry methods – JUPAS (Joint University Programmes Admission Scheme) and non-JUPAS. Students who complete the Hong Kong Diploma of Secondary Education (HKDSE) are categorised as JUPAS and all other students admitted are categorised as non-JUPAS.
4. GPA is a weighted average of the grades a student accumulates. Calculating GPA involves multiplying each numeric grade for a subject by its credit-point value, taking the sum and then dividing by the total number of credit points taken. At our university, GPA can range from 0 to 4 and is calculated on a semester and yearly basis, as well as at the end of the program (Award GPA).

Author Details

Christine Armatas
christine.armatas@polyu.edu.hk

Christine Spratt
christine.f.spratt@polyu.edu.hk