Extracting Learning Performance Indicators from Digital Learning Environments

Sundaramoorthy, Prem ; Vertegaal, Cornelis; Martinez, Cecilia; Serra, Ramiro; Verhoeven, Chris; Montagne, Anton; Bentum, Mark J

DOI
10.1109/EDUCON52537.2022.9766395

Publication date
2022

Document Version
Final published version

Published in
Proceedings of the 2022 IEEE Global Engineering Education Conference (EDUCON)

Extracting Learning Performance Indicators from Digital Learning Environments

Prem Sundaramoorthy
Department of Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
p.p.sundaramoorthy@tue.nl

Cornelis Vertegaal
Department of Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
c.j.c.vertegaal@tue.nl

Cecilia Martinez
School of Education
National university of Córdoba
Cordoba, Argentina
cecimart@gmail.com

Ramiro Serra
Department of Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
r.serra@tue.nl

Chris Verhoeven
Department of Microelectronics
Delft University of Technology
Delft, The Netherlands
c.j.m.verhoeven@tudelft.nl

Anton Montagne
Department of Microelectronics
Delft University of Technology
Delft, The Netherlands
anton@montagne.nl

Mark Bentum
Department of Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
m.j.bentum@tue.nl

2022 IEEE Global Engineering Education Conference (EDUCON) | 978-1-6654-4434-7/22/$31.00 ©2022 IEEE | DOI: 10.1109/EDUCON52537.2022.9766395

***Abstract*— In the last decades, there has been a steady adoption of digital online platforms as learning environments applied to all levels of education. This increasing adoption forces a transition in educational resources which has further been accelerated by the recent pandemic, leading to an almost complete online-only learning environment in some cases.**

The aim of this paper is to outline the methodology involved in setting up a framework for mapping course-specific data based on student activity to standard learning indicators, which will serve as an input to performance prediction algorithms. The process involves systematically surveying, capturing, and categorising the vast range of data available in digital learning platforms. The data are collected from two sample courses and distilled into five dimensions represented by the generic learning indicators: *prior knowledge, preparation, participation, interaction,* and *performance.* The data is weighted based on course development and teaching member's perspectives to account for course-wise variations. The framework established will allow portability of prediction algorithms between courses and provide a means for meaningful and directed learner formative feedback.

Two courses, both bachelor-level and worth 5 European Credits (ECs), that use several online learning platforms in their teaching tools have been chosen in this study to explore the nature and range of student interaction data available, accessible, and usable in a course. The first course is Electromagnetics II at Eindhoven University of Technology, and the second course is Electronics at Delft University of Technology. Both Universities are located in the Netherlands.

This work is in the scope of a broader study to use such learning indicators with predictive algorithms to provide a prognosis on individual student performance. The findings in this paper will enable the realization of student performance prediction at a very early stage in the course.

Keywords—Learning indicators, learning analytics, data portability, student progress monitoring, student prognosis, early warning

I. Introduction

The last years have seen a growing presence and acceptance of digital online platforms in education. The recent pandemic has dramatically forced this adoption as many education institutions, left with no choice, had to rapidly adapt to remote online education [1]. Digital Learning Environments (DLE), albeit, a bit forced in the current circumstances, offer some key opportunities with respect to capturing student activity through interactions between students and the platform. These interactions have the potential to add valuable insight into student learning strategies and associated effectiveness[2]–[4].

The ubiquitous use of interactive digital learning environment implies vast amounts of tracking data that can be leveraged for early warning systems and understanding other learning elements. Additionally, since the data collection in a digital platform is not a separate act but rather a non-intrusive record of interactions, the data collected are an authentic representation of student behaviour[5]. A review on the literature of e-learning systems concludes that a successful e-learning system should consider the personal, social, cultural, technological, organizational, and environmental factors[6].

However, the use of learning analytics has raised some concerns as well. In a study that compared 17 blended courses within a single institution involving close to 5000 students, results of predictive modelling strongly vary across courses and the portability of prediction models across courses is rather low [4]. The study also emphasized the need to include more specific theoretical argumentation and additional data sources other than just the data from Learning Management Systems (LMS). Furthermore, authors have reported contradicting correlations of certain data predictors related to online activity [7]. The study concludes that learning analytics should allow for pedagogical variations and that learning analytics are likely to be effective in reliably enhancing learning outcomes only if they are designed to track data that are genuine indicators of learning.

In this paper, to overcome these limitations, we propose a methodology of mapping course-based data to generic learning indicators that accounts for individual course design and teaching perspectives and is based on proven learning indicators. The four key steps that outline the process are listed below.

1. Establishing a list of generic learning indicators that identify with learning strategies and learning approaches.

2. Making a comprehensive list of course-specific student interactions that can be captured in the specific learning environments and collaboration platforms.

3. Mapping these course specific interactions to generic learning indicators based on teaching members' perspectives.

4. Deriving indices corresponding to these learning dimensions that can serve as a standard input to prediction algorithms.

The paper is structured as follows. Section II briefly introduces the Automated Prognostic Student Progress Monitoring System (APSPMS) project under which the scope of this work is done. This is followed by an outline of the two pilot courses: Electromagnetics II (EM II) at Eindhoven University of Technology and Electronics at Delft University of Technology, chosen for this project. The generic learning indicators are established and discussed in Section IV. This is followed by the methodology for mapping course-based data indicators to generic learning indicators and thence to generic indices, in Section V. The paper concludes with a discussion on potential advantages, limitations, and next steps.

II. Project Background and Paper Scope

The work presented in this paper are initial steps towards a more comprehensive project to develop an Automated Prognostic Student Progress Monitoring System (APSPMS) that shall continuously track, assess, and monitor a student's comprehension (as dictated by the course learning objectives) throughout the course schedule, from start to finish. The APSPMS, at any point during the course, makes use of the gathered information to predict the student's performance and serves as a prognosis towards the result a student would achieve at the end of the course assessment. The system shall also generate formative feedback to the student and prescribe concrete actions that would lead to a better final result.

The outline of the APSPMS project is shown in Fig. 1. A modular approach is taken, distinguishing between two domains: the course-specific part (where student-interaction data in an individual course is extracted and categorized) and the more generic part (algorithm development for predicting student performance from generic learning indicators). There are three reasons for this approach – a) Having a standalone prediction algorithm part will ensure seamless portability of this part to other courses, with development needed only in the course-specific part, making the system more scalable, b) This allows traceability of the predicted performance to meaningful learning indicators rather than just data activity, and, c) The intermediate set of generic learning indicators will allow a reference for comparing data richness of different course learning environments.

The APSPMS project is currently being piloted at two technical universities (Eindhoven University of Technology and Delft University of Technology) in two courses, enabling to find solutions that are more general, leading to a more modular system that can be scaled easily. The scope of this paper is restricted to exploring the data available from the corresponding learning environments, establishing the set of generic learning indicators, and qualitatively mapping course-specific interactions to the generic indicators and thence deriving corresponding indices.

III. Characteristics & Specifications of the Pilot Courses

Table 1 details the main characteristics and specifications of the two courses chosen for this study. The courses use a considerable number of digital platforms to support the different learning activities that have been developed to

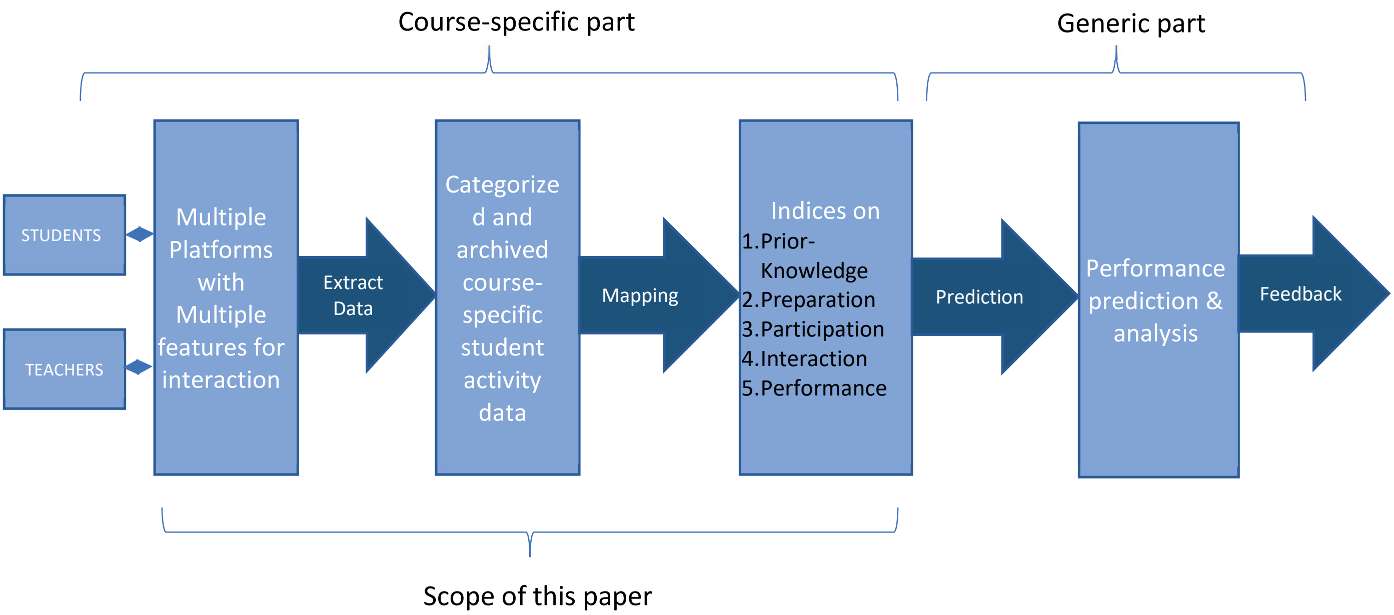

Fig. 1. APSPMS Project outline and the scope of this paper

enable the students in achieving the intended learning objectives.

Table 1. Specifications of the Pilot courses

Courses selected for Pilot	Course 1	Course 2
University	Eindhoven University of Technology	Delft University of Technology
Department	Electrical Engineering	Electrical Engineering
Course Name	Electromagnetics II	Electronics
Level	BSc.	BSc.
EC	5	5
Period	Q4 – April to July	Q3 – February to April
Expected number of students	300	120
Teaching methods	Student led tutorials	Lectures
	Lectures	Tutorials
		Instructor led design sessions
Assessment methods	Optional midterm	Exam
	Student led tutorials	Assignments
	Written exam	Quizzes
		Design Report
Digital platforms	Canvas (LMS)	BrightSpace (LMS)
	Microsoft Teams	YouTube (Lecture recordings)
	Zoom (Q&A)	Zoom (Q&A)
	Discord (discussions)	
	Panopto (video hosting and streaming)	
	MediaSite (video hosting and streaming)	

IV. Generic Learning Indicators

The behaviour of students captured by the online platforms and their interaction with the learning material, peers or teachers could add significant insight into the learning processes involved[8]. However, these interactions captured as raw data, need to be channelled through a theoretically grounded set of general learning indicators (GLIs). The GLIs are a set of dimensions or indicators representing student features or actions and have the potential to strongly influence the learning outcome. In this work, through literature evidence and personal teaching experience, we have identified the following GLIs: *prior knowledge, preparation, participation, interaction,* and *performance* as the five GLIs that strongly influence a student's progress and achieved learning outcome.

Some educational psychologists have long claimed that the most important single factor influencing learning is what the learner already knows[9], [10]. Therefore, prior knowledge is included as a prime candidate in the list of generic learning indicators. Studies have shown that student engagement is critical in achieving a high learning outcome, and many measures of engagement are linked positively with desirable outcomes like critical thinking and grades[11], [12]. The work of Lee summarised the literature findings on student engagement that the important indicators of engagement are learning effort, participation, interaction, cognitive task solving, learning satisfaction, sense of belonging, and learning passion. Student engagement has been measured in multiple ways, with self-report being the predominant option for the latter four indicators. Since our primary interest is in exploiting the non-intrusive data collected by the digital platform, we restrict ourselves to the first three indicators of engagement. In this work, engagement is seen as a composition of three elements – preparation (that represent the student's learning effort), participation, and interaction.

We define student performance, both in formative and summative assessments at varying times through the course as the fifth and final general learning indicator. The five generic learning indicators along with their intended usage in this paper are outlined in Fig. 2.

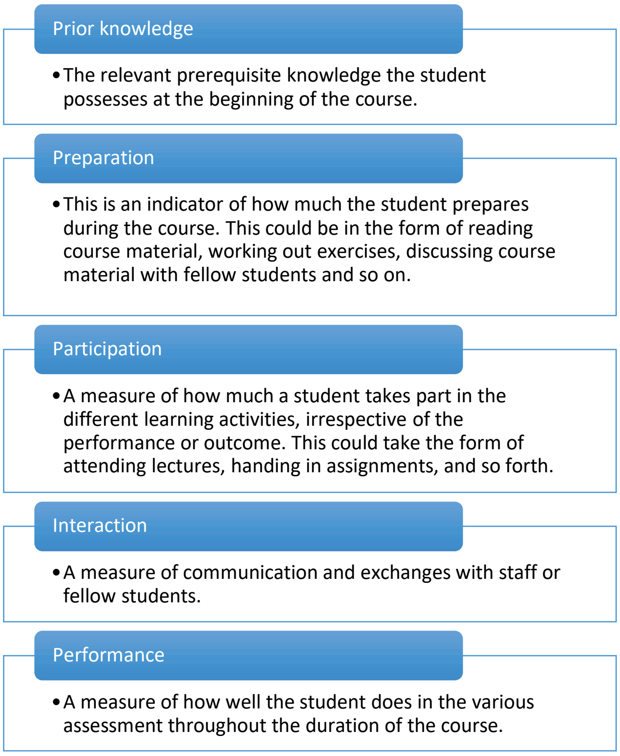

Fig. 2. The five generic learning indicators along with their explanations.

V. Mapping Course-Based Data to Generic Indices

The aim is to derive indices, along each of the learning indicators or dimensions discussed in the previous section, that will serve as inputs to the prediction model. Courses typically have one or more learning activities such as lectures, tutorials and so on. Furthermore, each of these activities are divided into components, for example, lectures could have an associated reader, live lectures, video recordings and maybe more elements. Data points or instances corresponding to these components have been identified, extracted, and categorized. These data instances are then subjected to a normalized double-weighted process to derive the generic indices. The table is formed by aggregating the perspectives of teaching members involved in the course.

The steps involved in the mapping process are outlined below. The first two steps result in a data map for the two courses as shown in Tables 2 and 4. The third step is used to derive the indices from the data map and will be used as input to the prediction process.

A. Activity weighting

A course is composed of one or more learning activities. The activity weighting is done to establish the relative importance of the different activities (as seen by the teaching members) with respect to the course learning outcomes.

B. Data point weighting

As illustrated in Table 2, there are several data points that are available from the learning environment. The magnitude of these data points can provide pointers along the different learning indicators. These weights are a measure of how well a specific data point represents a particular learning dimension.

C. Index Scaling

As a final step to derive the generic indices, the double weighted data points are scaled with respect to the maximum value possible along each GLI. This scales the indices to a fixed range (zero to one) across different courses.

For a given course with N activities, and each activity having q_i $(i = 1{:}N)$data points, we have

$$GI_k = \frac{\sum_{i=1}^{N} W_i \left(\sum_{j=1}^{q_i} \omega_{ijk} P_{ij}\right)}{\sum_{i=1}^{N} W_i \left(\sum_{j=1}^{q_i} \omega_{ijk}\right)}$$

where, GI_k is the index corresponding to the k^{th} *GLI*, W_i is the weight of the i^{th} activity, P_{ij} is the normalised magnitude (zero to one) of the i^{th} activity's j^{th} data point, and ω_{ijk} is the weight of P_{ij} along GLI_k. From Table 2, for the EM-II course, N = 3, and q = (6,7,5). From Table 4, for the Electronics course, $N = 3$, and q = (7,3,4).

This ultimately results in five indices along the five GLIs for each student. These indices quantify the generic indicators that can be derived for any course and ported into the prediction model to derive prognosis. It should be noted that all the data in Table 2 and Table 4 are not available from the start of the course, making the GIs a function of time. Additionally, the implication of the data resolution (individual or group) should be addressed in the prediction process.

In Table 2, we see the data map for the EM-II course, constructed from nine respondents - two teachers (course developers, coordinators and strongly involved in all activities in the course) and seven teaching assistants. In this case, the individual responses were averaged, and the associated standard deviations for the different values can be found in Table 3. Table 4 is formed by a discussion and consensus between the two teachers (course developers, coordinators and strongly involved in all activities in the course) in the course, and therefore, there are no standard deviations associated with these values.

The data maps provide a snapshot of the type and range of data available in the two courses. It gives a clear picture of the data collected and to what extent they reflect generic indicators of learning. From Tables 2 and 4, we can observe in both the courses, by summing the GLI columns in the data maps, that *prior knowledge* and *interaction* are the least represented compared to the other indicators. These insights can be very useful for both, prediction approaches and data collection strategies.

Investigating the different data points in the two courses, by summing row-wise ($\sum_{k=1}^{5} \omega_{ij}$), it can be observed that the top data point (the point that leads to the maximum for $\sum_{k=1}^{5} \omega_{ij}$, corresponding to a data point that represents the GLIs, aggregated, to the highest extent)) for the EM II course is 'TAs perception of how well the session went' closely followed by ' Ratio of students speak time to staff speak time', both from the student-led tutorial activity . For the Electronics course the top two data points are 'Grade (Assignments)' and ' Grade (Design Report)', both falling under the assessment activity. Incidentally, all the four data points have a group resolution.

VI. Discussion and Conclusion

A. Data map as a measure of data richness

The data map provides a snapshot of the data richness that a course learning environment provides. The breadth of data available with respect to the different learning indicators as well as the associated effectiveness of these data in predicting learning outcome is captured in a single table. Therefore, the data map serves as an excellent tool to assess data gaps, a framework for cross comparison between courses, and a standardized pathway to predicting learning outcome. It can also aid during course resource allocation with a priority assessment with respect to data collected. Additionally, developing such data maps serve as a means for course designers and teachers to reflect on the different components in the course and how students benefit from them.

B. Activity and data weights to factor in course variations

Aggregating the weights from teaching members involved in the course ensures that pedagogical variations in a course are accounted for. Furthermore, these weights are associated with variances which can be used either for selecting the raw data that form the indices or for additionally ranking the data points. The variances can also be propagated to calculate the variance in the GIs, enabling a confidence estimation of the prediction.

C. GLIs as an effective channel for prediction and feedback

Five generic learning indicators, namely, *prior knowledge, preparation, participation, interaction,* and *performance* have been identified as potential predictors of student progress and achieved learning outcome. The GLIs serve as a standard set of parameters that can be derived from any course and fed as input to prediction algorithms. This allows portability of prediction algorithms to multiple courses. Furthermore, having these distinct GLIs ensures that student feedback can be classified along the same dimensions. Therefore, a student gets feedback at the level of participation, interaction and so forth rather than on raw data activity.

The initial findings show that online platforms provide a convenient access to data points associated with student interaction that can be mapped to indicators of learning strategy. The data maps can provide insight on how existing teaching activities can be modified, and new ones can be added to enhance data richness and fidelity. Every course is unique in its structure, organization, and delivery and this significantly influences student learning approaches and strategies. These, sometimes subjective, course-dependent flavours and features significantly determine the importance of the different student interactions. The framework proposed in this paper provides a means to inject this valuable bias into the prediction process.

In conclusion, the methodology presented in this paper, to map raw data available in a course's digital learning environment to a set of generic indicators, can pave the way for a student progress monitoring and feedback framework that is theoretically grounded and portable to multiple courses.

Table 2. EM II course data map with a selected list of data points. Activity weight represents the relative importance of the learning activity, with zero corresponding to no importance and 10 corresponding to extreme importance. The numbers along the GLIs indicate how well the magnitude of the corresponding data point represents the GLI, with zero corresponding to no representation and 10 to extremely high representation. The cell colours are scaled based on the cell values.

Course Activity [i]	Activity Weight $[W_i]$	Components	Platform	Data point $[P_{il}]$	Data Resolution	Data weights along Generic Learning Indicators $[\omega_{ijk}]$				
						Prior Knowledge	Preparation	Participation	Interaction	Performance
Lectures	6.88	Reader	Canvas	Number of times accessed	Individual student	2.44	7.89	4.56	1.00	3.78
		Lecture Slides	Canvas	Number of times accessed	Individual student	2.56	8.11	6.33	2.00	4.78
		Exercises	Canvas	Number of times accessed	Individual student	2.11	8.67	7.33	2.89	5.67
		Videos	https://videocollege.tue.nl.	Number of times viewed	Individual student	4.11	7.11	5.44	1.89	3.67
				Time spent		5.38	7.50	6.00	1.88	4.50
				Pauses		3.25	3.63	2.75	1.63	1.63
Student-led Tutorial	9.00	SLT Exercises	Canvas	Time accessed	Individual student	2.44	7.22	7.44	2.44	5.56
		Exercises prepared (SLT Ticks)	Recorded in Excel	Number of exercises prepared	Individual student	2.25	8.75	8.38	5.13	8.13
				Time at which readiness is conveyed	Individual student	0.13	4.63	4.25	1.13	3.38
		Session - Audio recording	Microsoft Teams	Ratio of students speak time to staff speak time	Group	2.44	6.11	9.00	9.33	6.44
		Student Discussions	Discord	Number of messages between students		2.44	6.22	8.33	8.67	5.56
				Number of messages between students and staff		2.88	6.13	8.00	8.00	5.25
		SLT TA reflection	Canvas	TAs perception of how well the session went	Group	4.11	7.33	8.67	8.56	6.44
Assessments	7.25	Pre-test	Recorded in Excel	Grade	Individual student	9.00	5.44	3.56	1.11	7.11
		Mid-term Exam (Voluntary)	Recorded in Excel	Choice to participate	Individual student	3.56	5.78	7.56	2.11	6.22
				Grade		5.38	7.50	5.75	2.00	8.38
		Final Exam	Recorded in Excel	Grade	Individual student	3.11	8.44	6.56	2.67	9.56
		Resit	Recorded in Excel	Grade	Individual student	3.22	7.89	5.67	2.56	9.22

Table 3. Standard deviations corresponding to the EM II course data map in Table 2.

Course Activity [i]	Std. dev. of the Activity weights [σ_{W_i}]	Components	Platform	Data point [P_{ij}]	Data Resolution	Standard deviation of the Data weights [$\sigma_{\omega_{ijk}}$]				
						Prior Knowledge	Preparation	Participation	Interaction	Performance
Lectures	1.46	Reader	Canvas	Number of times accessed	Individual student	2.70	1.76	3.64	1.58	2.86
		Lecture Slides	Canvas	Number of times accessed	Individual student	2.13	1.17	3.16	2.18	3.83
		Exercises	Canvas	Number of times accessed	Individual student	2.15	1.32	2.45	3.10	3.57
		Videos	https://videocollege.tue.nl.	Number of times viewed	Individual student	2.26	2.15	3.88	2.20	2.87
				Time spent	Individual student	1.92	1.31	3.42	2.47	2.93
				Pauses	Individual student	2.82	3.96	3.41	2.92	2.00
Student-led Tutorial	0.89	SLT Exercises	Canvas	Time accessed	Individual student	3.09	1.86	1.81	2.30	3.32
		Exercises prepared (SLT Ticks)	Recorded in Excel	Number of exercises prepared	Individual student	2.38	1.67	1.92	3.14	1.96
				Time at which readiness is conveyed	Individual student	0.35	4.10	4.68	2.10	3.93
		Session - Audio recording	Microsoft Teams	Ratio of students speak time to staff speak time	Group	2.79	3.82	0.87	0.87	2.35
		Student Discussions	Discord	Number of messages between students		2.30	2.64	1.94	2.00	2.30
				Number of messages between students and staff		2.75	2.59	1.93	2.00	2.43
		SLT TA reflection	Canvas	TAs perception of how well the session went	Group	3.22	2.40	0.87	0.73	3.13
Assessments	2.56	Pre-test	Recorded in Excel	Grade	Individual student	1.00	2.46	3.09	1.96	2.71
		Mid-term Exam (Voluntary)	Recorded in Excel	Choice to participate	Individual student	3.40	3.96	2.13	3.22	4.12
				Grade	Individual student	2.07	2.14	2.76	3.21	0.74
		Final Exam	Recorded in Excel	Grade	Individual student	3.10	1.51	3.24	3.61	0.73
		Resit	Recorded in Excel	Grade	Individual student	3.03	1.45	3.84	3.43	1.09

colour scale

0 · · · · · · · 2.5 · · · · · · · · · 5

Table 4. Electronics course data map with a selected list of data points. Activity weight represents the relative importance of the learning activity The numbers along the GLIs indicate how well the magnitude of the corresponding data point represents the GLI The cell colours are scaled based on the cell values.

Course Activity [i]	Activity Weight [W_i]	Components	Platform	Data point [P_{ij}]	Data Resolution	Data weights along Generic Learning Indicators [ω_{ijk}]				
						Prior Knowledge	Preparation	Participation	Interaction	Performance
Lectures	5	Recommended book (pdf)	Course website	Number of downloads	Group	0	2	3	0	0
				Time of download	Individual	1	4	3	0	0
		Videos	YouTube	Number of views	Group	7	7	4	0	0
				Percentage of video viewed	Group	7	7	5	0	0
				Channel subscription	Individual	0	8	8	2	0
		Lecture Slides	BrightSpace	Number of times accessed	Individual	2	3	3	0	0
				Time of access	Individual	2	5	4	0	2
Tutorials	8	Simulation software	Brightspace	Time of download	Individual	0	8	5	0	2
		Q&A session	Zoom	Teacher's estimation of quality of work	Individual/Group	8	8	8	8	8
		Self-enrolment	BrightSpace	Enrol action	Individual	0	3	10	10	3
Assessments	10	Assignments	BrightSpace	Grade	Group	4	5	8	8	9
		Quizzes	BrightSpace	Grade	Individual	4	4	4	3	9
		Exam	BrightSpace	Grade	Individual	3	6	4	0	9
		Design Report	BrightSpace	Grade	Group	5	5	10	10	10

colour scale

0 · · · · · · · · · 5 · · · · · · · · · 10

Acknowledgment

The authors would like to thank all the respondents of the EM II data map survey for their inputs. This project is funded partially by the Netherlands Initiative for Education Research (NRO) through the Comenius programme's 'Senior Fellow' grant, and partially by the Eindhoven University of Technology through the 'Be the Owner of your Own Study' (BOOST) program.

References

[1] C. Y. Mo, T. H. Hsieh, C. L. Lin, Y. Q. Jin, and Y. S. Su, "Exploring the critical factors, the online learning continuance usage during covid-19 pandemic," *Sustainability (Switzerland)*, vol. 13, no. 10, May 2021, doi: 10.3390/su13105471.

[2] N. Buniyamin, U. bin Mat, and P. M. Arshad, "Educational data mining for prediction and classification of engineering students achievement," in *2015 IEEE 7th International Conference on Engineering Education, ICEED 2015*, Apr. 2016, pp. 49–53. doi: 10.1109/ICEED.2015.7451491.

[3] Greller, Santally, Boojhawon, Rajabalee, and Sungkur, "Using Learning Analytics to Investigate Student Performance in Blended Learning Courses," *Zeitschrift für Hochschulentwicklung*, vol. 12, no. 1, Mar. 2017, doi: 10.3217/zfhe-12-01/03.

[4] R. Conijn, C. Snijders, A. Kleingeld, and U. Matzat, "Predicting student performance from LMS data: A comparison of 17 blended courses using moodle LMS," *IEEE Transactions on Learning Technologies*, vol. 10, no. 1, pp. 17–29, Jan. 2017, doi: 10.1109/TLT.2016.2616312.

[5] W. Greller and H. Drachsler, "Translating Learning into Numbers: A Generic Framework for Learning Analytics," *Educational Technology & Society*, vol. 15, pp. 42–57, Jul. 2012.

[6] T. Katoua, M. AL-Lozi, and A. Alrowwad, "A Review of Literature on E-Learning Systems in Higher Education," *International Journal of Business Management and Economic Research*, vol. 7, pp. 754–762, Jan. 2016.

[7] A. Wilson, C. Watson, T. L. Thompson, V. Drew, and S. Doyle, "Learning analytics: challenges and limitations," *Teaching in Higher Education*, vol. 22, no. 8, pp. 991–1007, Nov. 2017, doi: 10.1080/13562517.2017.1332026.

[8] L. K. M. Poon, S. C. Kong, T. S. H. Yau, M. Wong, and M. H. Ling, "Learning analytics for monitoring students participation online: Visualizing navigational patterns on learning management system," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2017, vol. 10309 LNCS, pp. 166–176. doi: 10.1007/978-3-319-59360-9_15.

[9] D. P. Ausubel, J. D. Novak, and H. Hanesian, *Educational psychology: A cognitive view*, vol. 6. holt, rinehart and Winston New York, 1968.

[10] J. A. C. Hattie and G. M. Donoghue, "Learning strategies: a synthesis and conceptual model," *npj Science of Learning*, vol. 1, no. 1, Dec. 2016, doi: 10.1038/npjscilearn.2016.13.

[11] J. Lee, H. D. Song, and A. J. Hong, "Exploring factors, and indicators for measuring students' sustainable engagement in e-learning," *Sustainability (Switzerland)*, vol. 11, no. 4, Feb. 2019, doi: 10.3390/su11040985.

[12] R. M. Carini, G. D. Kuh, and S. P. Klein, "Student engagement and student learning: Testing the linkages," *Research in Higher Education*, vol. 47, no. 1, pp. 1–32, Feb. 2006, doi: 10.1007/s11162-005-8150-9.