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Learning, Data and Methodological Approaches - Qualitative, Quantitative or Mixed Methods Dilemmas?

Don Passey
Professor of Technology Enhanced Learning
Director, Centre for Technology Enhanced Learning
Director, Doctoral Programme for e-Research and Technology Enhanced Learning
Department of Educational Research
Lancaster University

Summary of this presentation

- A bit of background – my involvement with data and learning
- Data analysis and learning
- Methodological approaches and research design
- Aims and intentions
- Data and stakeholders
- Example studies
- Data about extents of reported research approaches
- Conclusion

Data analysis and learning

- Learning can be considered as processes that can be grouped into three main categories (Child, 1973; Passey, 2014)
  - Internalisation – the ways we engage with ideas, concepts, knowledge and details from our external environment or existing internal thoughts
  - Internal cognitive processes – the ways we handle those ideas, concepts, knowledge and details, and use them to build on, support or review our existing knowledge and concepts
  - Externalisation – the ways we make our learning known to others, through different external routes
- So what data (or learning analytics) are needed to gain insights into these processes?
- Can we assume that one form of data about one of these categories can inform us about one or more learners, or provide insights for one or more users (teachers, advisors, policy makers, etc.)?

Methodological approaches

- Data and methodological approach should be intrinsically linked, and to the end audience of the research:
  - Action research implies the researcher is the user
  - Design-based research implies the developers are the users
  - Case studies imply an organisation, or group, or individual is the user
  - Phenomenology implies looking for variations in a group
- These approaches have little to do with whether the data are quantitative or qualitative, whether they are analysed in quantitative or qualitative ways, or presented in quantitative or qualitative ways
- The ‘what’, the ‘why’ and the ‘how’ can all be important
- ‘Extents and levels’ and ‘explanations’ may all be worthwhile

Research design

- There needs to be a clear link between a study's:
  - Rationale and its purpose (aims and intentions)
  - Prior studies and insights
  - Research questions
  - Methodological approach
  - Data gathering methods and tools
  - Data analysis
  - Presentation of findings
  - Audience

- How do learning analytics fit with matters of research design?

Aims and intentions

- The aims of using data can be varied
- Some categories are:
  - Exploring the use of data gathering tools
  - Developing data analysis tools
  - Providing visualisations of ideas or outcomes
  - Providing visual interpretations of findings
  - Providing feedback for other researchers
  - Providing feedback to specific users, including students and teachers

- How do learning analytics fit with aims and intentions?

What data do stakeholders need from data or learning analytics?

- Policy makers – Overviews? Options? Averages? Outliers?
- Educational advisers – Gaps? Issues? Exceptions?
- Head teachers or principals – Overviews? Comparisons?
- Teachers – Group views? Individual views? Outliers?
- Parents – Individual views? Comparisons?
- Students – Individual analyses? Personalised?
- Educational software developers – Successes? Averages?

- Macro, meso and micro levels (Buckingham-Shum, 2012)

Example study 1

- “Learning analytics have been applied to study and visualize the relationship between student activity and performance in online-based university-level courses during the last decade
- “The authors of 11 relevant studies published in peer-reviewed scholarly journals all found some benefits, but they also cited many problems when trying to assess student learning through combinations of learning analytics, learning management system (LMS) activity data logs, and graded performance results
- “All 45 participants were undergraduate students in an upper division Professionalism Seminar and Human Resource Management (HRM) course taught by the researcher”

Source: Strang, 2016

Example study 1 - visualisation

Table 1. Descriptive Statistics of Sample and Moodle Engagement Analytics (*N* = 45).

	Dispersion		Correlation						
Variables:	Mean	*SD*	Age	Gender	Culture	L	A	F	C
Age	20.31	1.635							
Gender, 0 = F, 1 = M	0.58	0.499	−0.169						
Culture, 1 = international	0.51	0.506	−.307*	−0.026					
(L) Lessons (views)	8.33	4.690	0.128	−0.152	−0.141				
(A) Engage assignment	0.69	0.063	−0.176	0.208	0.256	−.310*			
(F) Engage forum	0.98	0.137	−.437**	0.176	0.154	0.108	−0.007		
(C) Engage course login	0.49	0.065	−0.082	0.201	0.163	−.369*	.783**	0.061	
Grade (out of 100%)	0.76	0.309	−0.043	0.01	−0.073	0.294	−.566**	−0.087	−.577**

*Correlation significant at the .05 level (2-tailed).
**Correlation significant at the .01 level (2-tailed).

Source: Strang, 2016

Example study 2

- “The purpose is to explore the relationships between student grade and key learning engagement factors using a large sample from an online undergraduate business course at an accredited American university (n = 228)
- “The final size of this sample was 228 students who were drawn from several sections of the same courses taught by two professors (one was the author), all undergraduate students in an upper division Professionalism Seminar and Human Resource Management (HRM) course”

Source: Strang, 2016

Example study 2 - visualisation

- H4: Course logins from Moodle engagement analytics (EngageC) have a positive causal relationship with student learning (Grade);
- H5: Forum postings identified by Moodle engagement analytics (EngageF) have a positive predictive relationship with student performance (Grade).
- H6: Assignment activity identified by Moodle engagement analytics (EngageA) have a positive predictive relationship with student performance (Grade);
- H7: Lesson reading activity identified by Moodle system logs (LessonR) have a positive predictive relationship with student performance (Grade);
- H8: Lesson quiz activity identified by Moodle system logs (LessonQ) have a positive predictive relationship with student performance (Grade);
- H9: Lesson quiz scores identified by Moodle system logs (LessonS) have a positive predictive relationship with student performance (Grade);

Table 3 GLM of key factors regressed on dependent variable grade ($n = 228$)

Predictors	Coefficient	SD	T	P	VIF	Hypothesis
Constant	18.516	2.47	7.5	0		
Engage C	0.08785	0.03236	2.71	0.007	2.4	H4 accepted
Engage F	0.0271	0.1113	0.24	0.808	481.8	H5 rejected
Engage A	0.0038	0.1062	0.04	0.971	480.7	H6 rejected
Lesson R	0.16442	0.03599	4.57	0	2.5	H7 accepted
Lesson Q	0.38682	0.03928	9.85	0	2.5	H8 accepted
Lesson S	0.13205	0.03409	3.87	0	2.2	H9 accepted

Source: Strang, 2016

Example study 3

- Figure 4 displays nodes and edges “contained in a circular area, which is especially useful to analyze student and teacher active behaviors on a per classroom basis
- It “shows the interactions in each classroom, with the size of each node corresponding to the number of new messages posted by each student; except for classroom 10, the node with a higher number of new posts represents the consultant teacher
- It “provides useful information about how many students are weakly connected with the rest – i.e. which students have read few messages, or none, which could be an early warning sign of an at-risk student
- Figure 5 node colours indicate “final grade – from green to yellow, students who passed the continuous assessment; from orange to red students who failed to pass the continuous assessment; gray nodes are students who did not finish the course; white nodes are the consultant teachers – and node size representing weighed out-degree – i.e. how many posts did each student read”

Source: Hernández-García, González-González, Jiménez-Zarco and Chaparro-Peláez, 2015

Example study 3 - visualisation

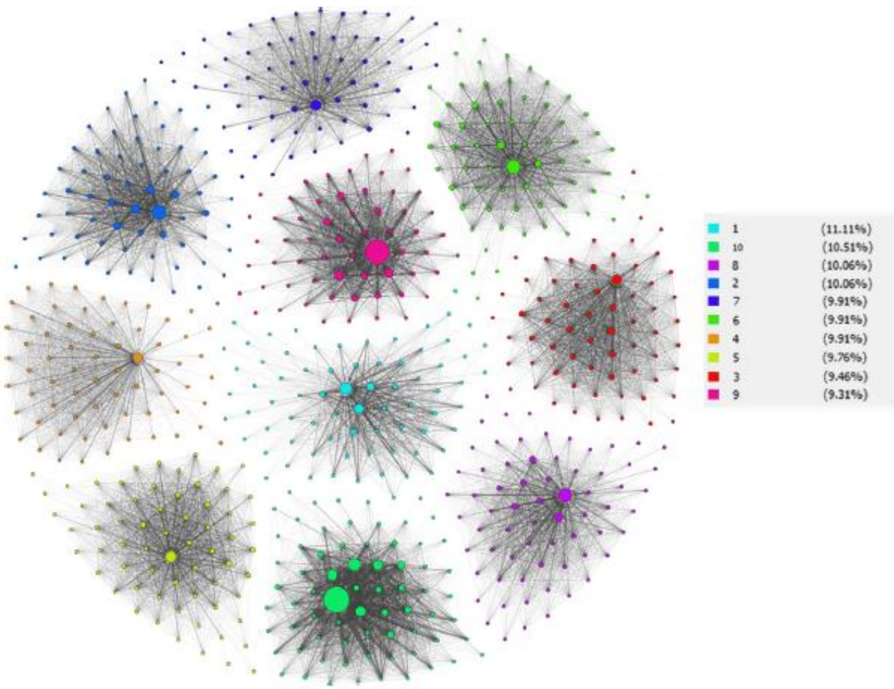

Fig. 4. "Read" network by classroom and number of sent messages.

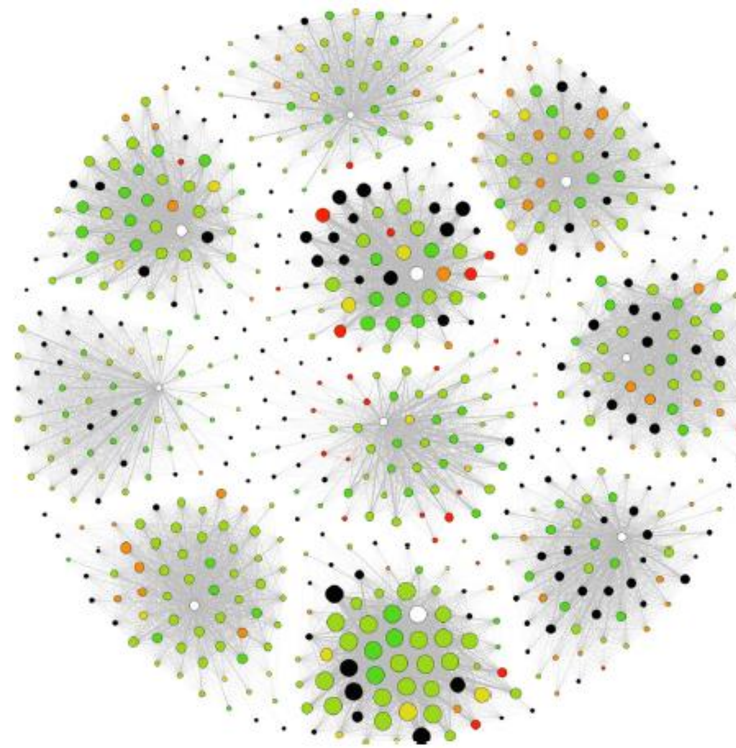

Fig. 5. "Read" network by weighed out-degree and final grade.

Source: Hernández-García, González-González, Jiménez-Zarco and Chaparro-Peláez, 2015

Data about extents of reported research approaches

- From the Lancaster University Library One-Search online journal access tool, the following numbers of articles were f

Focus of the article	Results found
Learning analytics quantitative approaches	31
Learning analytics qualitative approaches	36
Learning analytics mixed methods approaches	7
Learning analytics case studies	721
Learning analytics design-based research	165
Learning analytics action research	531
Learning analytics student outcomes	686
Learning analytics teacher support	117
Learning analytics longitudinal studies	26

Conclusions

- Learning analytics are expanding the possibilities of methodological approach
- This does not mean there is necessarily a need to distinguish always between quantitative and qualitative approaches; research design is more crucial as a factor
- Data visualisation is becoming increasingly important and is being enhanced in terms of formats and user engagement
- Stakeholder needs are important if research is not to just inform other researchers, and to meet some national 'performance' needs
- Data analysis and presentation should be considered as means to support discussion prior to decision making wherever relevant (Passey, 2013)
- Many studies appear to be focused on short-term rather than longer-term findings and their implications and interpretations
- Learning analytics appear to be focusing on social engagement and interaction as much as on subject outcomes, grades or levels; whether correlations have any causality is yet to be fully argued

References

- Buckingham-Shum, S. (2012). *Learning analytics [policy brief]*. Moscow, RU: United Nations Educational, Scientific and Cultural Organization (UNESCO) Institute for Information Technologies in Education. Retrieved from http://iite.unesco.org/pics/publications/en/files/3214711.pdf
- Child, D. (1973) *Psychology and the teacher*. London: Holt, Rinehart and Winston.
- Hernández-García, Á., González-González, I., Jiménez-Zarco, A.I. and Chaparro-Peláez, J. (2015). Applying social learning analytics to message boards in online distance learning: A case study. Computers in Human Behavior, 47, 68-80.
- Passey, D. (2013). At the Heart of the Next Generation of Information Technology in Educational Management: Data Driven Discussion Making. In D. Passey, A. Breiter, and A. Visscher (Eds.). *Next Generation of Information Technology in Educational Management.* Springer: Heidelberg, Germany.
- Passey, D. (2014). *Inclusive Technology Enhanced Learning: Overcoming Cognitive, Physical, Emotional and Geographic Challenges*. Routledge: London.
- Strang, K.D. (2016). Do the Critical Success Factors From Learning Analytics Predict Student Outcomes? *Journal of Educational Technology Systems, 44*(3), 273-299.
- Strang, K.D. (2016). Beyond engagement analytics: which online mixed-data factors predict student learning outcomes? *Education and Information Technologies*. doi:10.1007/s10639-016-9464-2

Thank you for listening!

Contact
d.passey@lancaster.ac.uk