

Integrating Learning Analytics, Survey Self-Reports, and Qualitative Data: Insights from Two Pilot Studies

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New sources of data: challange and opportunities

• New digital sources of data might redefine the role of traditional methods of data collection (JAPEC et al., 2015)

 Hence it can also impact MM research perspectives and designs (HESSE-BIBER & JOHNSON, 2013)

Big Data

AAPOR Task Force Report on Big Data	0 🖈
Big Data in Survey Research and Official Sta	
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Frauke Kreuter	IUSUCS
Frauke Kreuter AAPOR – Webinar 2016	ausucs

AAPOR REPORT: BIG DATA February 12, 2015

Prepared for AAPOR Council by the Task Force, with Task Force members including:

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Student workload research

Workload as time an individual spends on learning activities

- Workload is viewed as an essential component of student effectiveness (BERGER & BAUMEISTER, 2016)
- The Bologna Reform made workload one of the central pillars of the comparability (ECTS USERS' GUIDE)
- Workload is often measured with survey selfreport (duration questions)



New source of data: Learning Analytics

"...the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs"

(as cited in LONG & SIEMENS, 2011, p. 34)



New source of data: Learning Analytics

- ...relies on "pre-existing, machinereadable data" (FERGUSON, 2012, p. 305)
- ...can also be called: Organic data Passive data Unobtrusive data
- ...is mostly used to predict dropouts and disengagement



Total Enrolled Learners



Example: LA provided by Coursera (for instructors)

Student Workload: LA vs. survey self-report

Survey Data

+ traditionally used in workload measurement

BUT

- Social desirability
- Recall-error
- Non-response

LA Data

- + Unobtrusive measure
- + No problem with non-response
- + No social desirability

BUT

- Cannot measure (at least directly) subjective states
- Limited transparency

Can LA substitute survey self-report to measure student workload?

• Quantitative Data:

Integration of LA and survey self-report

- Qualitative Data:
 - cognitive & semi-structured interviews
 - goes beyond pre-testing and instrument development
 - serves the purpose of evaluating data quality (data generating process & construct validity)
 - helps inform the way LA and survey self-report data can be integrated

AUFSTIEG DURCH Federal Ministry International Program in Survey and Data Science (IPSDS) of Education OFFENE HOCHSCHULEN and Research 2. Model Eval Validation HW 2 Assignment January 12, 2016 Mediasite Presenter Course #1: 8:58 PM,Feb 21 3. K-Means Clustering Man Kaiwen HW 2 Assignment January 12, 2016 Mediasite Presenter _ 🗆 🗙 16 Students (n=192): Homework Assignment 1 3. K-Means Clustering 🖄 data file for homework r Tasks for Homework Nu 6 0 www.jpsmclasses.umd.edu/Mediasite/Play C Q Search ☆自 Ø \equiv 12 Weeks (Feb-Mai, 2016) Quiz 2 HW Number 1 Solutions Focus: video-watching This is a .R file that can be opened using **Machine Learning Methods/Techniques** using Notepad or other text editor (or Wo tasks of HW 1. There are many different machine learning methods available Many are non-parametric in nature and while a functional form can be specified, it is generally not a natural byproduct of the method Week 3 • Wu et al. (2008) provide an overview of ten of the top machine Bluejeans Join Meeting [Tuesday, 02/16/ learning algorithms including (see http://bit.ly/1liWTir) : Course #2: 🐩 🖩 K-means Clustering PageRank (1) 4. K-Nearest Neighbors K-nearest neighbors 13 Students (n=143): January 12, 2016 Mediasite Presenter Support Vector Machines Decision Trees and Classification and Regression Trees 🛐 5. CARTS Apriori Algorithm January 12, 2016 Mediasite Presenter The EM Algorithm (Expectation-Maximization) Naïve Bayes 11 Weeks (June-August, 2016) HW 2 Assignment Ensemble Methods (like AdaBoost and Random Forests) Tasks for HW Number 2 00000101000001010100000100111101010000 Small Course B 💋 Datasets for HW 2 Focus: video-watching V Quiz 3 HW 2 Solutions Playing 1x Here is the R script file containing the sol 02:15 / 44:08

Can LA substitute survey self-report to measure student workload (video watching)?

Survey self-report

LA

Step 1: Quantitative:

- Survey and LA data
- Collected weekly (12/11 weeks)
- Parallel
- Integration (Survey and LA): Analysis

Cognitive Interviews

Semi-structured Interviews

Step 2: Qualitative:

- 2 types of interviews
- Collected within the same session at the end of 2 courses
- Integration (Quant & Qual):
 Interpretation

Data Source #1: Learning Analytics

• collected via *Mediasite* software (external provider)

Username	Views	Total time watching	Time covered	% Watched	Length
A	1	00:14:00	00:10:00	100%	00:10:00

Data source #2: Weekly survey self-report (web-based)

During the past week, how much time did you spend (in hours) on the activities below?

If you don't know precisely, then please provide your best estimate.

Watching pre-recorded lecture videos	
Doing required readings	
Doing recommended readings	
Completing course assignments	
Discussing course topics with other participants outside of the BlueJeans meetings	
Other course-related work	
Paid Work	
Household chores	
Child care	
Leisure	

Workload (in Minutes): Video-Lecture

Course:	Mean	Median	SD	Range
#1 Fundamentals				
LA (viewing activity log)	73.54	74	46.04	295
Survey (self-report)	161.25	120	100.57	480
#2 Data Collection				
LA (viewing activity log)	56.96	59.52	45.04	165.82
Survey (self-report)	120.86	120	67.60	300

Course #1

Count



Fundamentals: LA

300

Course #2

Data Collection: Self-Report



Data Collection: LA



cor(LA, self-report)

within_`var' = `var' - mean_`var'

Course	Between correlations	Within correlations
Course #1	0.14	0.17*
Ν	15	168
Course #2	0.04	0.38**
N	12	132

* 5% ** 1%

"Sanity Check": Correlation with grades

Course/Data Source	Between correlations	Within correlations
Course #1		
(12 Homework assignments)		
LA	0.24	0.04
Self-Report	0.02	0.02
Ν	15	180
Course #2		
(7 Homework assignments)		
LA	-0.06	0.14
Self-Report	-0.16	0.19
Ν	12	84

• significant at 10% level

Qualitative data

- Cognitive and semi-structured interviews were conducted within the same sessions
- Conducted online (via Bluejeans online video-conferencing system)
- All students were invited to participate via email
- 3 out of 16 did not respond
- Transcription: complete
- Analysis: Qualitative content analysis



Data Source #3: Cognitive Interviews (Survey Data Quality)

Cognitive Interviews:

"...to evaluate the quality of the response or to help determine whether the question is generating the information that its author intends" (BEATTY & WILLIS, 2007)

General Probes:

"During the spring and summer semester, you were invited to participate in the weekly evaluation survey where we asked you (among others) about time spent on watching pre-recorded lecture videos. How hard was it for you to answer that question?"

Think Aloud:

(Participant is asked to think aloud while answering).

"During the past week, how much time (in hours) did you spend on watching prerecorded lecture videos?"

Data Source #4: Semi-structured interviews (LA Data Quality)

"Could you describe me your typical way of watching video lectures in [name of the course]?"

Probes:

• Elaboration and clarification probes (if necessary)

Prompts:

- Pausing to "digest" the material or other purposes
- Taking notes during or after the video

Data Source	Mean(SD)	Qualitative Data:
Survey self-report		
Course #1	161.25 (100.57)	Understanding problems: week calender or unit-based
Course #2	120.86 (67.60)	
LA		
Course #1	73.54 (46.04)	
Course #2	56.96 (45.04)	

Data Source	Mean(SD)	Qualitative Data:
Survey self-report	•	
Course #1	161.25 (100.57)	Understanding problems: week calender or unit-based
Course #2	120.86 (67.60)	 Recall problems: 2 estimation strategies
LA		
Course #1	73.54 (46.04)	
Course #2	56.96 (45.04)	

Recall strategies:

Based on the event:

"I remember it was exactly 1 hour, because I had 1 hour before the meeting started. And on Wednesday, also I came home at I think it was 6:30 and I had to leave quarter past eight, so I had about 2 hours. It was easy, because video watching time was framed by other things I had to do."

• Based on the recalled length of the videos:

"I watched all the videos once, so it was around 90 minutes. I remember that there were 6 or 7 and all of them lasted about 8-15 minutes. Well, then it is not such a good estimate. I don't know 90 minutes or 2 hours, that's what popped up in my head, but if you think it through I don't think I spent that much time as 90 minutes. I think it was less."

Data Source	Mean(SD)	Qualitative Data:
Survey self-report	·	
Course #1	161.25 (100.57)	Understanding problems: week calender or unit-based
Course #2	120.86 (67.60)	Recall problems: 2 strategies to recall
LA		
Course #1	73.54 (46.04)	Some participants reported taking notes during watching
Course #2	56.96 (45.04)	the video (hence pausing)

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Course #1	73.54 (46.04)	Some participants reported taking notes during watching
Course #2	56.96 (45.04)	 the video (hence pausing) Possibility of downloading the videos

Conclusion I:

- Qualitative data provided insights on data generating process of both LA and survey data (otherwise unavailable)
- Although LA provides more precise estimate of workload for video watching, it also has notable data quality problems (downloading)
- Workload construct: LA=playing the video; Survey=engaging with the video lecture
- Qualitative Data \longrightarrow LA and survey data can complement each other

Conclusion II:

- Challenges and limitations for big data projects:
 - sampling for qualitative interviews;
 - qualitative data collection and analysis is time intensive, a potential problem, since found data can rapidly change
 - ethical questions (e.g. data linkage)
 - collaborative approach (team work)

Literature

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Thank you.