LEARNING ANALYTICS IN HIGHER EDUCATION: SCOPE, USE, AND IMPLICATIONS

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ABOUT ME

Doctoral Candidate, George Mason University

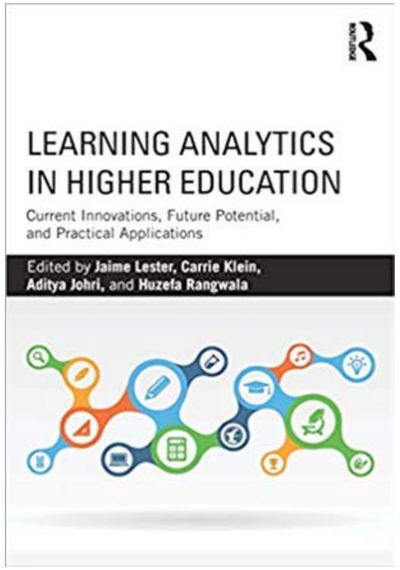
Research:

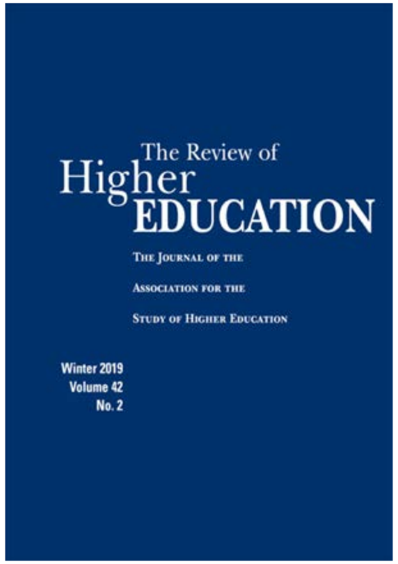
- NSF Big Data Grant (2015-2018)
- NSF IUSE Grant (2019-2020)
- CGS Summer Researcher (2017)

AERA Division J Graduate Representative (2017-2019)

Writing (Analytics-Related):

- 2 published peer-review articles (first author) *The Review of Higher Education* & *Journal of Computing in Higher Education*
- 3 articles under review (2, first author)
- Edited book (co-editor)
- Monograph (second author)
- 2 edited book chapters (first author)
- Forthcoming NACUBO Business Officer Magazine article
- 1 (in progress) dissertation





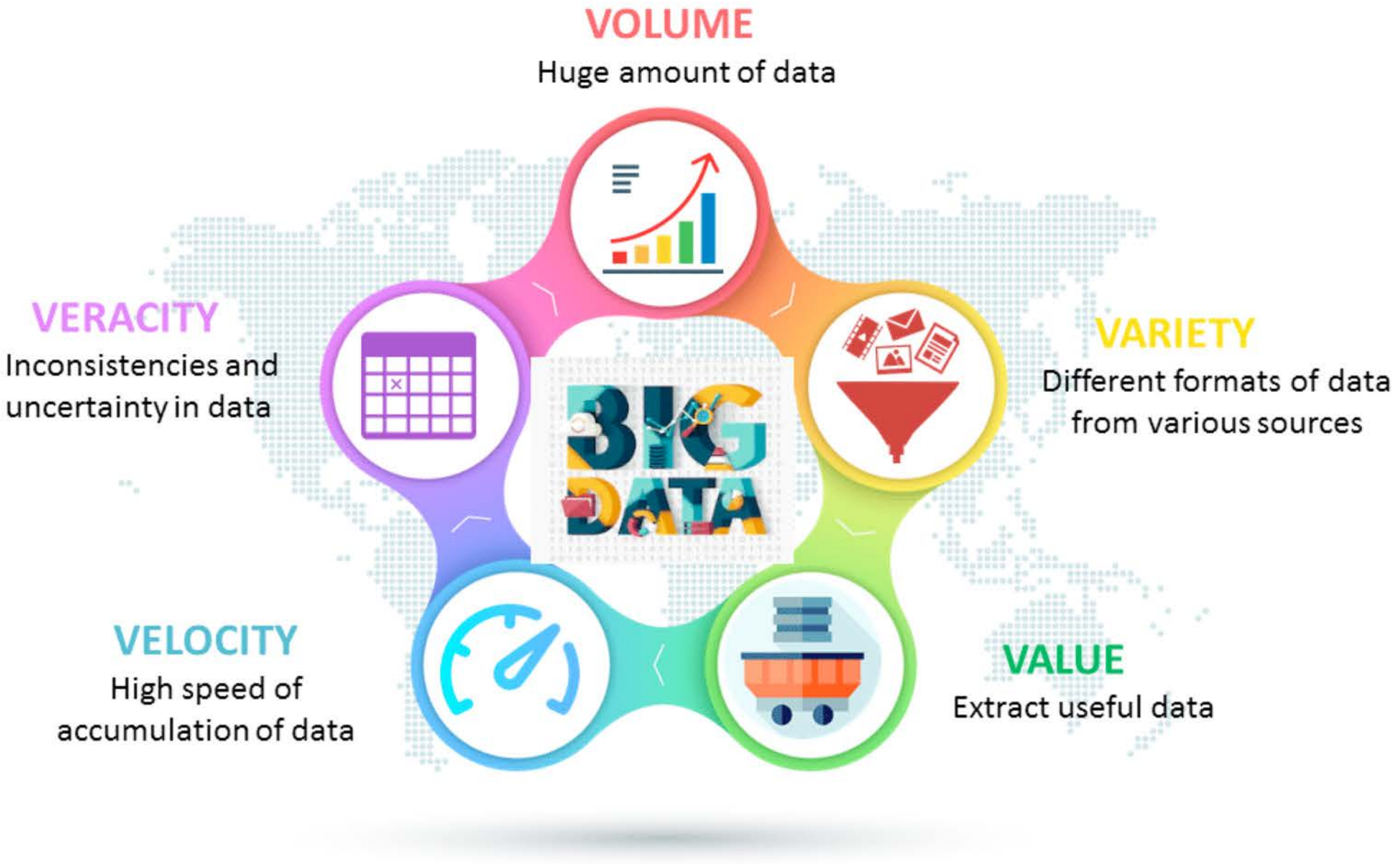
TODAY'S AGENDA

- Learning Analytics and Big Data Definitions and Overview
- How Learning Analytics Technologies Work
- Context and Potential of Analytics
- Examples of Current Technologies and Outcomes
- Complexities and Implications in Use

WHAT IS LEARNING ANALYTICS?

"Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs"

(Siemens, 2013, p. 3).



Source: Edureka

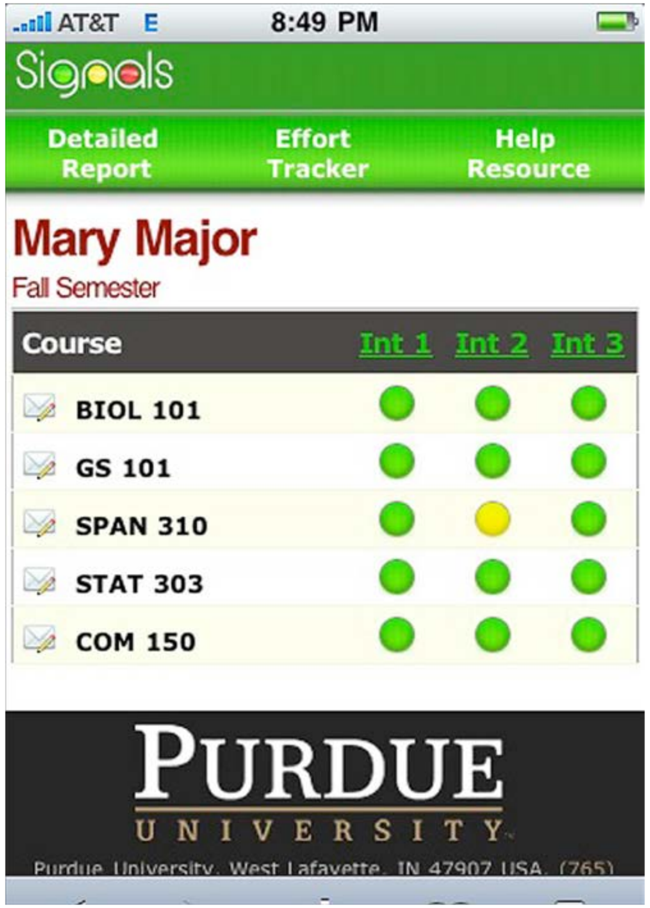
TABLE 1: LEARNING AND ACADEMIC ANALYTICS

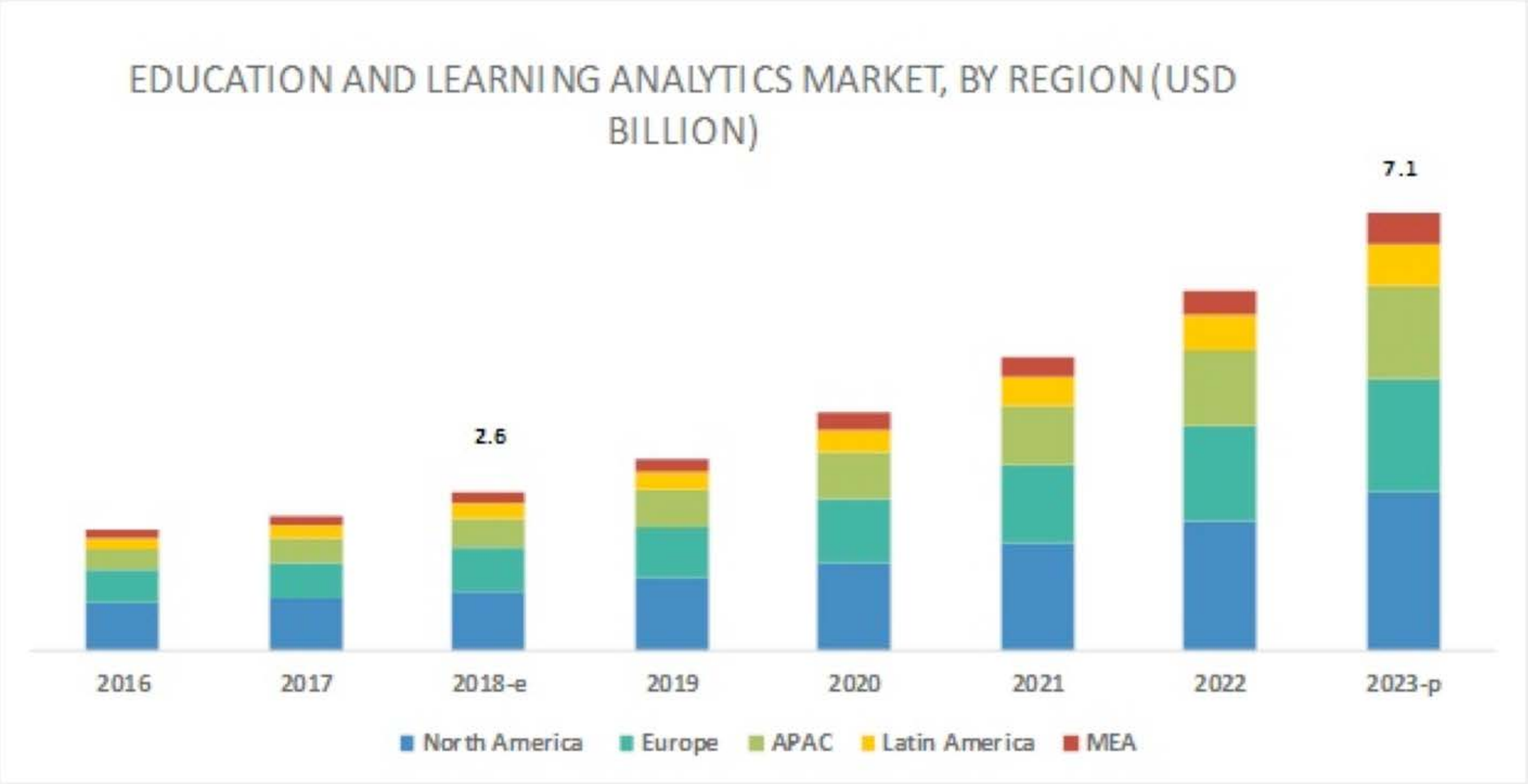
TYPE OF ANALYTICS	LEVEL OR OBJECT OF ANALYSIS	WHO BENEFITS?
Learning Analytics	**Course-level:** social networks, conceptual development, discourse analysis, "intelligent curriculum"	Learners, faculty
	Departmental: predictive modeling, patterns of success/failure	Learners, faculty
Academic Analytics	**Institutional:** learner profiles, performance of academics, knowledge flow	Administrators, funders, marketing
	Regional (state/provincial): comparisons between systems	Funders, administrators
	National and International	National governments, education authorities

Source: Siemens and Long (2011)

HOW LEARNING ANALYTICS WORK

- **Large variable datasets**
- Underlying **algorithms** make **correlations and predictions** based on weighted variables (demographic, performance, interaction & historical and contemporaneous)
- **Visualized data interventions** sent to faculty, advisors, and (sometimes) students **via dashboards** to **identify students at risk** of dropping or failing a course or not registering or completing





e: estimated; p: projected
Source: MarketsandMarkets Analysis

WHY THE EXPONENTIAL GROWTH?

ENVIRONMENT

- Increased oversight and accountability
- Decreased funding
- Completion agenda
- Shifting models of higher education
- Technological advancements

POTENTIAL

- Improved decision-making
- Improved student retention and completion
- Clearer course and career pathways
- Formative and holistic assessment
- Greater insight into trends and resources

EXAMPLES OF LEARNING ANALYTICS TECHNOLOGIES

Georgia State University

800+
ANALYTICS-BASED
ALERTS

10 YEARS OF DATA | **2.5 MILLION** GRADES

144,000
STUDENT RECORDS

30,000 STUDENTS TRACKED DAILY

COMPLEXITIES IN USE

- Organizational
- Technological
- Individual
- Ethical

TECHNOLOGICAL

- Limited empirical evidence of effectiveness (learning assessment)
- Unclear if retention/completion gains for EWS are a result of tech or associated structural changes (combination of factors)
- Lack of integration across systems (LMS, EWS, SIS, etc.)
- Lack of transparency/clarity of black box systems and their algorithms
- Lack of user inclusion and perspective in development and design
- Scalability within and across higher education organizations
- Correlation ≠ causation (and higher probability of spurious correlation with big data)

ORGANIZATIONAL

- Organizational capacity and readiness
  - Infrastructure, resources, culture, context, and commitment
- Lack of clearly defined policies, frameworks, communications for use
- Lack of training and professional development for users
- Uneven buy-in or inclusion in organizational decision making
- Limited resources and infrastructure limit efficacy of learning analytics

INDIVIDUAL

- Variability in interest, desire, or need (or willingness to change)
- Variability in incentives and rewards
  - Institutional roles and socialization have a large influence
- Variability in trust of data
  - Usually based on prior experience
  - Data visualizations influence
  - For students, interventions must come from a trusted source
- Time to incorporate into practice is a major barrier (especially for faculty)
- Concerns about riskiness or accuracy of predictive data

ETHICAL

- Algorithmic bias and opacity
  - 'Baked-in' and hidden bias has the potential to discriminate and reaffirm structural inequities
  - What variables are being used to determine which outcomes and for whom?
- Unclear data use and ownership in MOUs/contracts between tech and orgs
- Limited or antiquated data governance and use policies and practices in organizations
  - Needed updates in data security, access, and management policies
  - Unclear parameters for general or repurposed data use or data use after affiliation ends

IMPLICATIONS FOR ETHICAL & EQUITABLE USE

- Improved data governance and use policies
  - Acknowledge and account for nature of big data
  - MOUs that require transparency of tech and data ownership
- Improved training and development
  - For all users on how to interpret and use analytics data
  - Graduate programs in computer science & data science must include a greater focus on ethics and equity (not just privacy protection)
- Understand optimal data, delivery, structure, support, & resources for analytics success
- Inclusive framework for equitable use of learning analytics data and research
  - Rooted in data justice, care, and agency
  - Centers student inclusion, rights, education, and empowerment over their data

QUESTIONS & CONVERSATION

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