LEARNING ANALYTICS FROM READINESS TO IMPLEMENTATION

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Open University of Hong Kong
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Overview

- Conceptual Framework
- Purposes of Learning Analytics
- Readiness for Learning Analytics
- Implementation & Application
  - Examples
  - Challenges
  - Ethical Considerations
- Broad Potential
Examining Learning Analytics

- What, specifically, is the role of learning analytics in education?
- Can learning analytics enrich the student experience?
  - To what extent?
- Is it possible to use learning analytics to increase retention/graduation/success?
- To what extent can learning analytics contribute to successful outcomes?
Conceptual Framework

ANALYTICS

- Business Analytics
- Academic Analytics
- Learning Analytics
- Predictive Analytics
- Actionable Intelligence (Action Analytics)
- Decision-making

van Barneveld, Arnold, & Campbell, 2012

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Conceptual Framework

- Expanded
- Broader
- Reflective

van Barneveld, Arnold, & Campbell, 2012
What do Analytics Involve?

- Technology infrastructure, tools, and applications
- Policies, processes, and practices
- Skills of faculty, staff, students, and other stakeholders
- Culture and behaviors
- Leadership at the institutional level
But to what end?

- Increase faculty to student communication
- Increase student awareness of class standing and eventual outcome
- Involve advisors in student success efforts
- Instigate behavior change among
  - Students
  - Faculty/Instructors
  - The broader institution
Why?
HERE’S WALDO!

Each dot represents one of the 68 locations of Waldo in the seven primary Where’s Waldo? books. A point labeled B2P5 means it is Waldo’s location in book two on page five.
Purposes of Learning Analytics

- Create “actionable intelligence” (Campbell, DeBlois, & Oblinger, 2007) in the “here and now” (Siemens & Long, 2011)
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- Curriculum Design (Dunbar, Dingle, & Prat-Resina, 2014)
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- Enhance the teaching/learning environment (Lockyer, Heathcote, & Dawson, 2013)
- Improve student performance (Arnold & Pistilli, 2012) and student learning (Clow, 2013)
- Predict performance of students (Kellen, 2013)

\[ y_i = \beta_1 X_1 + \beta_2 Z_1 + e_i \]
Analytics is about

- Actionable intelligence
- Moving research to practice
- Basis for design, pedagogy, self-awareness
- Changing institutional culture
- Understanding the limitations and risks
What we know...

“The institutional application of analytics *can* result in a major shift for colleges and universities with regard to the culture fostered around undergraduate learning.”

Pistilli, Willis, & Campbell, 2014, p. 88
The Digital Ocean

http://i.imgur.com/YWObh.jpg
Change begets change.
What is Readiness?
readiness
('red-ē-nis)

noun

1 willingness to do something.
2 the state of being fully prepared for something.
3 immediacy, quickness, or promptness.
Readiness for Learning Analytics

- Readiness:
  - Is not a natural state
  - Will not happen accidentally
    - Logistics can be daunting
    - Innovative spaces can be challenging
  - Institutional reflection is critical
The Need for Reflection

- Comprehensive understanding
- Multiple perspectives needed
- Cross-disciplinary
- Diverse expertise & skills
- More realistic understanding of resources
- Limit bias that is inadvertently interjected
How to measure readiness?

Need:
- Comprehensive understanding
- Multiple perspectives
- Multiple levels

The Learning Analytics Readiness Instrument
Expansive Organizational Learning

- Moves from
  - abstract to concrete
  - simple relationships to multifaceted practices
- Grounded in theory of activity
  - Delineates the relationships between actors, tools, actions, rules, labor, and outcomes

Engeström, 1987; Engeström, Miettinen, & Punamäki, 1999
Organizational Learning

1. Questioning
   2a. Historical analysis
   2b. Empirical analysis

3. Modeling the new solution
4. Examining the new model
5. Implementing the new model
6. Reflecting on the process
7. Consolidating the new practice

Leont’ev, 1978; Engeström, 1995; Engeström, Kerosuo, & Kajamaa, 2007
Put differently...

- Identify a contradiction
- Find something that
  - Resolves it
  - or
  - Manages the situation “better”
- Broadly use the new solution
- Reflect
- Repeat
Institutional Aspects

- Three Critical Factors:
  1. Institutional factors (policies, promise; processes; progress)
  2. Program factors (teaching academic standards; graduate attributes; requirements; and learning outcomes)
  3. Individual factors (profile; motivations and aspirations; cultural context; work related factors)

- Each represent interacting activity systems in which students engage

- Contradictions can & will arise – exposing them yields opportunities to address the challenges as they’re identified.

Engeström, 2001
Overcoming Discontinuity

- Most projects have a clear start/end
- Usually gaps between projects
- Not all projects continue/relate to new efforts
- Important to bridge from one analytics project or implementation to the next
- Otherwise...
  - Momentum is lost
  - Desired transformation may not occur

“The LARI ... attempts to capture snapshots of institutional transition between each of these activities as well as their development for capacity among each crucial population of stakeholders.”

Oster, Lonn, Pistilli, & Brown, 2016
Framework for LARI Development

Parsimony

Practicality

Proactive
Survey Design

- Make changes
- Participate in LARI
- Reflect on results
- Obtain results
Survey Distribution Process

Alpha - 139 questions

• Reduced by factor analysis to 90 questions
• Original factors were: Ability, data, culture & process, governance & infrastructure, and overall readiness (Arnold, Lonn & Pistilli, 2014)

90 item survey was administrated (beta)

• Large group of stakeholders

Convenience sampling method

• From August 2014 to October 2014
LARI Beta Participants by Institution

- **Associate/Public-Research-Large, Baccalaureate-Arts & Science, & Baccalaureate-Diverse Fields**
  - 4 institutions
  - 84 respondents

- **Master’s Large & Research Universities (High Research Activity)**
  - 15 institutions
  - 337 respondents

- **Research Universities (Very High Research Activity)**
  - 5 institutions
  - 129 respondents

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LARI Beta Participants by Role

- Academic Dean/Faculty: 163
- Institutional Leader: 140
- IT professional: 109
- IR professional: 35
- SA Professional: 27
- Faculty Development: 19
- Other: 27
- Missing: 31
Factor Analysis

Exploratory Factor Analysis

- Principal axis factoring technique
- Only items on a five point scale
- Questions with over 70% response rate (removed 15 items)
- Questions regarding data collection were removed (5 items)

First factor analysis (unforced)

- 35 factors had eigenvalues of 1.0 or above
- 2 factors indicated by screeplot

Iterative process of forcing into 2, 3, 4, 5, etc. factors

- 5 factors produced the most sensible grouping of questions
Factor Analysis (cont’d)

Cleaning the factor analysis

• Items that were not loading were removed
  • all below |.30| (Tabachnick & Fidell, 2007).
• Items that were cross-loading were removed
  • above |.30| on multiple factors
• Iterative process

Sensitivity Check

• Conditional factor analysis for each institution type and role
• Factors, in general, hold
## Readiness Factors

<table>
<thead>
<tr>
<th>Factor</th>
<th># Survey Items</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Culture</td>
<td>22</td>
<td>“My institution has a culture that accepts the use of data to make decisions.”</td>
</tr>
<tr>
<td>Data Management Expertise</td>
<td>8</td>
<td>“My institution has the ability to store increasingly large volumes of data.”</td>
</tr>
<tr>
<td>Data Analysis Expertise</td>
<td>6</td>
<td>“My Institution has professionals with mathematical/statistical experience in manipulating and transforming data.”</td>
</tr>
<tr>
<td>Communication &amp; Policy Application</td>
<td>7</td>
<td>“My Institution has professionals with business acumen in marketing/publicity.”</td>
</tr>
<tr>
<td>Training</td>
<td>3</td>
<td>“My institution has professionals with customer-facing support experience in training constituents on the use of new systems.”</td>
</tr>
</tbody>
</table>
## Factors

### 46 items

- Cronbach's alpha of 0.956
- 87.74% of the variance explained

<table>
<thead>
<tr>
<th>Factor</th>
<th>Median</th>
<th>Skew.</th>
<th>Kurtosis</th>
<th>Alpha</th>
<th>Eigenvalue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Culture</td>
<td>3.27</td>
<td>-0.171</td>
<td>3.48</td>
<td>0.9169</td>
<td>15.57</td>
</tr>
<tr>
<td>Data Manage. Expertise</td>
<td>3.75</td>
<td>-0.294</td>
<td>2.94</td>
<td>0.9017</td>
<td>3.71</td>
</tr>
<tr>
<td>Data Analysis Expertise</td>
<td>4.00</td>
<td>-0.369</td>
<td>2.85</td>
<td>0.9559</td>
<td>2.16</td>
</tr>
<tr>
<td>Comm. and Policy App..</td>
<td>4.00</td>
<td>-0.633</td>
<td>4.38</td>
<td>0.9180</td>
<td>1.66</td>
</tr>
<tr>
<td>Training</td>
<td>3.67</td>
<td>-0.649</td>
<td>3.59</td>
<td>0.9140</td>
<td>1.27</td>
</tr>
</tbody>
</table>
## Results by Role

<table>
<thead>
<tr>
<th>Roles</th>
<th>Culture</th>
<th>Data Management Expertise</th>
<th>Data Analysis Expertise</th>
<th>Comm. &amp; Policy Application</th>
<th>Training</th>
</tr>
</thead>
<tbody>
<tr>
<td>Academic Deans/Faculty</td>
<td>-0.23**</td>
<td>-0.38***</td>
<td>-0.22*</td>
<td>-0.42***</td>
<td>-0.85***</td>
</tr>
<tr>
<td>Faculty Dev.</td>
<td>-0.15</td>
<td>-0.15</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.43*</td>
</tr>
<tr>
<td>Institutional Admin/Leaders</td>
<td>-0.09</td>
<td>-0.15</td>
<td>-0.12</td>
<td>-0.17*</td>
<td>-0.62***</td>
</tr>
<tr>
<td>IR Prof.</td>
<td>-0.28**</td>
<td>-0.16</td>
<td>0.10</td>
<td>0.18</td>
<td>-0.85***</td>
</tr>
<tr>
<td>SA Prof.</td>
<td>-0.14</td>
<td>-0.21</td>
<td>-0.08</td>
<td>-0.23</td>
<td>-0.73***</td>
</tr>
<tr>
<td>Other</td>
<td>-0.02</td>
<td>-0.20</td>
<td>-0.12</td>
<td>-0.19</td>
<td>-0.46*</td>
</tr>
<tr>
<td>Missing</td>
<td>-0.19</td>
<td>-0.20</td>
<td>0.01</td>
<td>-0.32**</td>
<td>-0.59***</td>
</tr>
</tbody>
</table>

Compared to IT professionals

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# Results by Institution

<table>
<thead>
<tr>
<th>Roles</th>
<th>Culture</th>
<th>Data Management Expertise</th>
<th>Data Analysis Expertise</th>
<th>Comm. &amp; Policy Application</th>
<th>Training</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assoc/Pub-R-L, Bac/A&amp;S, Bac/Diverse</td>
<td>-0.25***</td>
<td>-0.83***</td>
<td>-0.85***</td>
<td>-0.43***</td>
<td>-0.12</td>
</tr>
<tr>
<td>Master’s L, RU/H</td>
<td>0.27***</td>
<td>-0.15**</td>
<td>-0.43***</td>
<td>-0.15*</td>
<td>-0.07</td>
</tr>
</tbody>
</table>

Compared to RU - VH
Implications of the LARI

Practice Implications

• Validation of concepts through factor analysis
• Help pinpoint exactly where efforts should focus
• Know the institutional context

Institutional Learning

• Facilitates a conversation
• Culture is key for Learning Analytics
• Continuing iterative process
Implications of the LARI

Institutional Feedback

- Feedback is initial attempt to provide scaffolding for this process
- Needs to be normed to institutional characteristics
- Mindful of ethical issues
- Anecdotal evidence suggests that the feedback was helpful and useful
Moving Forward

Next Steps

• Production deployment
• Continued analysis of data and how institutions use the feedback

Major Takeaways

• Institutional roles and context matter when individuals are evaluating LA ability.
• Iterative process of organizational learning
• Only going to be become more prevalent so further engagement is needed
Implementing and Applying Analytics

- Necessary Components
- Examples
- Challenges
- Ethical Considerations
The Big Questions

- What can institutions do to improve student success?
- How can institutions help students take advantage of existing campus resources?
- What existing information on campus can be utilized to better identify students at risk?
- How can students become self-aware of what effort is necessary to be successful in college?
- How can analytics make a strategic impact at scale?
Implementation Considerations

- Alignment

Learning Analytics & Learning Activities

Wise, 2014
Implementation Considerations

- Alignment
- Integration

Goals

Expectations

Analytics

Activities

http://www.clipartbest.com/clipart-areRE/ef4

Wise, 2014
Implementation Considerations

☐ Alignment
☐ Integration
☐ Context

Wise, 2014
Reflection on Implementation

- Analytics MUST connect information provided to context in relevant & timely manners
  
  For meaning to be made by the learner

- “Omnipresent analytics” presents two dangers:
  1. Anytime/anyplace reviewing could yield nowhere/never
  2. Constant attention to metrics has students playing to the numbers, not engaging with learning

Wise, 2014
Examples

- Perceptions of an Early Warning System
- Self Regulation and Performance
- Predicting Performance
- Feedback usage and associated effects
- Effective Feedback
- Effective Implementation
Perceptions of Early Warning Systems

- Perceptions and Use of an Early Warning System
- Intentions ≠ Use
  - Intent: advisors use to identify students for intervention
  - Actual: advisors used during meetings with students
- Deconstructing/understanding visualizations are context specific and must be considered in the design
- Authoring representations of data must be sensitive to the needs of the intended and implied audiences.

Aguilar, Lonn, & Teasley, 2014
Self-regulation and Performance

- Relationship of Self-Regulation to Performance

- Takeaway:
  - Application of learning analytics is effective only if students are self-regulated enough to apply feedback.

Pardo, Han & Ellis, 2016
Predicting Performance

- Learning disposition matters
  - Effective dispositions include:
    - Deep learning approach
    - Ability to self-regulate
    - Setting learning goals
    - Intellectual curiosity

- High-risk vs. Low Risk

- Age

- Gender

Gray, McGuinness, Owende, & Hofmann, 2016
Predicting Performance (cont’d)

Considerations

- Self-regulation important but must be fostered
- Helping students learn effective positive learning dispositions possible and necessary

Gray, McGuinness, Owende, & Hofmann, 2016
Using Feedback

- Feedback usage and effects thereof
- Focused on use of a dashboard
- Key findings:
  - Use of the dashboard changes over time
  - No correlation between use & grades
  - Students want feedback, but couldn’t interpret a dashboard
  - More qualitative feedback necessary to drive academic improvement

Khan & Pardo, 2016
Effective Feedback

- Asked students what feedback they would like to see
- Five key components
  - Early & Often
  - Timely & Relevant
  - Substantive
  - Constructive & Encouraging
  - Message Construction Components

Arnold, Campbell, & Pistilli, 2012; Ehle & Gettings, 2013; Gettings, Waters, Selzer King, Tanes, & Pistilli, 2013
Early & Often

- Prompt feedback is important
- Late feedback is ineffective
- Multiple points of feedback

Chickering & Gamson, 1987; Hartley & Chesworth, 2000; Thompson & Mazer, 2009; Yorke & Longden, 2006
Timely & Relevant

- Feedback needs to be provided when useful
- Noting dates or events increases relevancy

http://s3.amazonaws.com/churchplantmedia-cms/vineyard_christian_fellowship/upcomingevents.jpg

Substantive

- Explicit
- Provides direct actions
- Focuses on outcomes of behaviors
- Puts the “action” in “actionable intelligence”

Gettings, Waters, Selzer King, Tanes, & Pistilli, 2013
Constructive & Encouraging

- Gains in Problem Solving
- Increases in Communication Skills
- More Effective
- Increased self-efficacy yields increased success
- Threatening feedback is ineffective
Message Construction

- We & you vs. I
- Demonstrate Concern
- High quality yields greater impact

Arnold, Campbell, & Pistilli, 2012; Ehle & Gettings, 2012; Gettings, Waters, Selzer King, Tanes, & Pistilli, 2013
Message Construction

- Short and Direct

- 62 words
- 52 words
- 40 words

Gettings, Waters, Selzer King, Tanes, & Pistilli, 2013
http://www.itap.purdue.edu/studio/passnote/
Ultimately...

- Seek to get:
  - The RIGHT information to
  - The RIGHT people in
  - The RIGHT way at
  - The RIGHT time
Effective Implementation

- Involves the following:
  - Information distribution
  - Data visualization and collection mechanisms
  - Knowledge of teaching and learning environments
  - Ability to collect, synthesize, and utilize data from student interactions with technology
  - Formative and learning outcomes assessment techniques

Greer, Molinaro, Ochoa, & McKay, 2016
Effective Implementation

- Learning analytics cannot be separated from the learning environment
- Outcomes must offer insights for both learners and educators (and institutions)
- Considers both generalized and boutique models
- Provides actionable information in light of institutional contexts
- Done where institutions are “ready,” e.g., have capacity and competencies

Gašević, Dawson, Rogers, & Gašević, 2015
Effective Implementation

- Involves student, staff, and faculty awareness.
- Creates practices, if not policies, around data use and governance.
-Strengthens mechanisms for feedback creation and delivery.
- Disseminates findings/results/outcomes to the broader campus and educational communities.

Boyd & Brack, 2014
Learning Analytics Challenges
Broad Challenges

- Accuracy & amount of data
- Timely reporting/use of data
- Face-to-face environments vs. Online environments
- Closing the loop
- Transparency
- Privacy
- Ethical considerations
Institutional Challenges

- Data in many places, “owned” by many people/organizations
- Different processes, procedures, and regulations depending on data owner
- Everyone can see potential, but all want something slightly different
- Sustainability — “can’t you just...?”
- Faculty participation is essential
- Staffing is a challenge
Ethical Considerations

http://3.bp.blogspot.com/-Gv_qJUJrWQ/UiZZP1FDU7I/AAAAAAAAA98/6MhsNnO_2-E/s1600/ethics.jpg
Ethics in a Learning Analytics Context

- “…systematization of correct and incorrect behavior in virtual spaces according to all stakeholders” (Pardo and Siemens, 2014, p. 439).

- Legal frameworks:
  - “transparency, student control over the data, security, and accountability and assessment” (Pardo and Siemens, 2014, p. 448).
Three Broad Categories

- The location and interpretation of data
- Informed consent, privacy and the de-identification of data
- The management, classification and storage of data

(Slade & Prinsloo, 2013)
Data Location

- Where is it?
- Who has it?
- Who has access to it?
- How is access granted?

https://foiaombudsman.files.wordpress.com/2012/04/scope.jpg
“The interaction between those that collect, hold, and utilize the data will set the tone as to how analytics will be fostered – or abandoned – at an institution.”

Pistilli, Willis, & Campbell, 2014, p. 88
Consent? Informed Consent? Just Informed?

- Are students **asked** what data can or cannot be used?

  OR

- Are students **told** what data will be used?
Consent? Informed Consent? Just Informed?

- Are students **asked** if data can be used?
- OR
- Are students **told** that their data will be used?
Limit Ad Tracking

Facebook Ads

- Ads based on my use of websites and apps: Can you see online interest-based ads from Facebook? No
- Ads on apps and websites off of the Facebook Companies: Can your Facebook ad preferences be used to show you ads on apps and websites off of the Facebook Companies? Yes
- Ads with my social actions: Who can see your social actions paired with ads? No one
- Ads based on my preferences: Manage the preferences we use to show you ads.

Opt Out

When you opt out, Google disables this cookie and no longer associates interest and demographic categories with your browser.

Your cookie

Google stores the following information in a cookie to associate your ads preferences with the browser you are currently using:

Visit the Advertising and Privacy page of our Privacy Center to learn more.
Opting... in or out...

Implied Contract?

- What are students paying for?
- What is expected of the institution?
You have agreed to our iData use Policy

http://lobby plag.eu/governments/topics
Contextual Integrity
Building Ethics into Every Step

- **Practical application is key**
- **Must include:**
  - probing questions
  - assessments of possible outcomes
  - active disagreement about future developments

Willis & Pistilli, 2014
Data Management, Classification, and Storage
Data Management

- Where is it?
- Who has it?
- Who has access to it?
- How is access granted?
- How is it linked to other sources?

https://foiaombudsman.files.wordpress.com/2012/04/scope.jpg
Obligation to Act

Are people willing to trade privacy for other benefits?

(Kay, Korn, & Oppenheim, 2012)
Obligation of Knowing

- Once something is known by someone at institution, what ethical obligations follow?

- What...
  - Options exist?
  - Is reasonable to do/change at this point in the semester?
  - What can actually be done?
Questions about Knowing

- Who is affected by the analysis or application of big data, and how should they be affected by it?
- Once a college's administration has the tools to "know" with statistical significance those who might be in jeopardy of failing, who is compelled to act on that knowledge?
- What action is appropriate based on the information learned as a result of the analysis?
- Who is responsible when a predictive analytic is incorrect?
Potential of Learning Analytics

- Rests in several things
  - Acceptance & Practice (Buckingham Shum, 2015)
  - Regular revisiting & reworking of models (Carleton, Mavrikis, & Katsifli, 2013)
  - Assessment of efforts (Clow, 2012)
  - Interoperability (Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012)
  - Ease of adoption and use (Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012)
  - Ethical frames and use (Willis, Pistilli, & Campbell, 2013)
Future of Learning Analytics

- Requires:
  - Building more collaborative environments
    - Institutions with institutions
    - Industry with institutions
    - Industry with Industry
  - Seeing learning analytics as a pedagogical approach
  - Recognizing what learning analytics can and cannot – should and should not - do
  - Having strong ethical principles and institutional policy around data collection and use
  - Realizing broad acceptance and adoption of data use
Concluding Thoughts

- Shifts in culture
  - Student success
  - What’s best for the student vs. faculty vs. institution
  - What the involved data actually is
- Focus on behavior change at all levels
- Leadership involvement from adoption to implementation through assessment
- User-friendly data collection, warehousing, and access
- Transparency
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