LEARNING ANALYTICS FOR TRACKING STUDENT PROGRESS

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In the following report, Hanover Research assesses learning analytics trends and use cases, with an emphasis on self-assessment or progress tracking data available to students. The report also includes best practices for developing and implementing learning analytics.

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EXECUTIVE SUMMARY AND KEY FINDINGS

INTRODUCTION

As institutions of higher education explore ways to develop cohesive technology-enhanced learning strategies, one important, emerging element of those strategies is learning analytics that supports students' self-assessment of their academic progress. In this report, Hanover Research assesses academic and professional literature on learning analytics at higher education institutions (HEIs). The report consists of the following sections:

- **Section I** provides an overview of institutional and learning analytics in higher education, including the overall analytics process, major types of analytics, common metrics collected to analyze student success, and implementation considerations.
- **Section II** presents several case studies that explore student-facing analytics initiatives that are designed to support learning and student success.
- **Section III** summarizes best practices and recommendations to consider when developing an institutional analytics strategy.

KEY FINDINGS

- **Although data analytics initiatives within higher education have traditionally focused on institution-wide applications, learning analytics is a growing area of interest for many HEIs.** Existing learning analytics initiatives are commonly connected to student performance monitoring efforts, including initiatives to improve retention, increase course completion, and reduce time to degree completion.
- **A successful analytics strategy draws input from key stakeholders at various levels and across disciplines.** Senior leaders can provide a strategic direction for and organizational commitment to learning analytics. Although technology departments are responsible for maintaining data, they should not be considered the sole source of expertise or responsibility. Data collection and analysis, as well as the potential for actionable outcomes, are optimized when a range of personnel from student support and administration, curriculum development, instruction, student resources (e.g., the library), and other units contribute.
- **Institutions should establish governance positions and procedures when developing an analytics strategy.** Data collection and management incur a number of risks and issues that require procedural standards and ongoing oversight. While universities may have existing structures, agreements, and processes for collecting and working with student data, these may not always fully cover new learning analytics implementations.

- **Specific governance considerations may include:**
  - *Data types to be used* for learning analytics and collection processes
  - *Anonymization* of the data where appropriate
  - *Analytics processes* to be performed
  - The *purpose or expected outcomes* of all analytical processes
  - *Retention and stewardship of data* used for and generated by learning analytics

- **Learning analytics dashboards often emphasize early warning systems.** Student retention is a concern at many HEIs, and therefore efforts to identify students at risk of failing and/or dropping out are a common learning analytics application. The majority of at-risk/early warning systems present information to instructors or student advisory personnel. However, some student-facing examples, such as Purdue University's Course Signals and Rio Salado College's RioPACE, offer a student interface to allow learners to track their performance and see whether they are on track or falling behind.

- **Student performance dashboards may incorporate anonymized peer data for self-comparison.** For example, University of Maryland Baltimore County's Check My Activity system displays a student's learning management system (LMS) use data, including sessions and hits, in comparison to average values from students who earned different scores on particular assignments and exams. The University of Michigan's gamified LMS system uses both comparative analytics and optional leader boards for students to "compete" with peers. The University of New England has a unique offering that aggregates student-reported feelings about subjects into a word cloud; this allows an overall view of how students' peers are feeling.

- **Student progress metrics primarily derive from learning management system data and are augmented by student records.** LMS data can be used to monitor student performance and engagement, while other student records can demonstrate academic history, student status, and broader engagement patterns outside the subject. Common metrics include:
  - *Academic performance data* (e.g., earned scores on assignments or exams)
  - *Student engagement data* (e.g., LMS session usage)
  - *Academic history* (e.g., secondary education GPA, standardized test scores, pre-university preparation)
  - *Characteristics* (e.g., enrolment status, academic track, demographics, financial aid status)
  - *Student self-reported information* (e.g., opinion or perception data, study plans, desired grades or course outcomes)

SECTION I: BACKGROUND AND TRENDS

Beginning in the 1960s, researchers began fusing computer science and statistics to perform complex analysis of digital data, a process alternately referred to as data science or data analytics.[1] As computing power and data storage space increased, organizations increasingly began to apply data analytics to their stores of member, customer, and industry data.

More recently, these data gathering and analysis techniques have extended into the educational sphere. Learning analytics (LA) can be defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs."[2] The increasing application of data analytics to learning is driven by several factors, including performance management and efficiency pressures, the increasing volume of data collected by institutions in the course of standard operations (particularly with the move toward more online and computer-assisted learning), and the wider availability of statistical and computational tools to manage large datasets and facilitate visualization or interpretation.[3]

THE ANALYTICS PROCESS

The learning analytics process operates as a cyclical progression of data collection, analysis, and action/intervention, derived from quality control techniques like continuous quality improvement (CQI).[4] Data immediately resulting from, or occurring after, interventions conducted in response to one phase of analysis are collected and fed into subsequent phases. Figure 1.1 illustrates the major stages in the learning analytics cycle.

Figure 1.1: The Learning Analytics Cycle
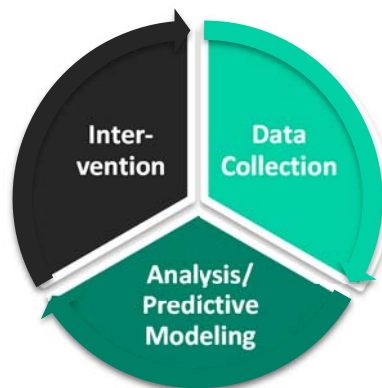
Adapted from: University of Florida[5] and Clow[6]

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[1] Press, G. "A Very Short History of Data Science." *Forbes*, May 28, 2013.
http://www.forbes.com/sites/gilpress/2013/05/28/a-very-short-history-of-data-science/

[2] *LAK '11: Proceedings of the 1st International Conference on Learning Analytics and Knowledge*. Banff, Alberta, Canada: ACM, 2011. p. 3.

[3] Clow, D. "An Overview of Learning Analytics." *Teaching in Higher Education*, 18:6, August 1, 2013. p. 5.

[4] "Learning Analytics: What It Is and Why It Matters." University of Florida Center for Instructional Technology & Training. http://citt.ufl.edu/online-teaching-resources/learning-analytics/

[5] Ibid.

THE LEARNING ANALYTICS LANDSCAPE

LEARNING ANALYTICS VERSUS INSTITUTIONAL ANALYTICS

As a whole, analytics used by educational institutions can cover a broad range of types, data sources, and areas for implementation. The broad types or focus areas for analytics within the higher education sphere can be divided into two major segments:[7]

INSTITUTIONAL/ACADEMIC
Emphasises performance of the university as a whole and tends to echo the frameworks, techniques, and purposes of Business Analytics. May incorporate learning performance data, but aggregated at the institutional, regional, or national level to illustrate performance of the university.

LEARNING
Emphasises the learning process, or the condition and performance of the individual learner. This type of analysis may be targeted toward the instructor and/or to the student himself or herself.

Data analytics within higher education has traditionally prioritized institutional or academic analyses. For instance, a 2015 EDUCAUSE survey of IT leaders at U.S. higher education institutions found that twice as many respondents reported institutional analytics as a major priority (47 percent) compared to learning analytics (23 percent).[8] Issues related to budget cuts may be driving this reliance on institutional data to maximize operational efficiency and better manage budgets. Figure 1.2 summarizes the priorities of 245 U.S. HE institutions regarding institutional versus learning analytics.

Figure 1.2: Priorities for Institutional and Learning Analytics at U.S. Universities, 2015
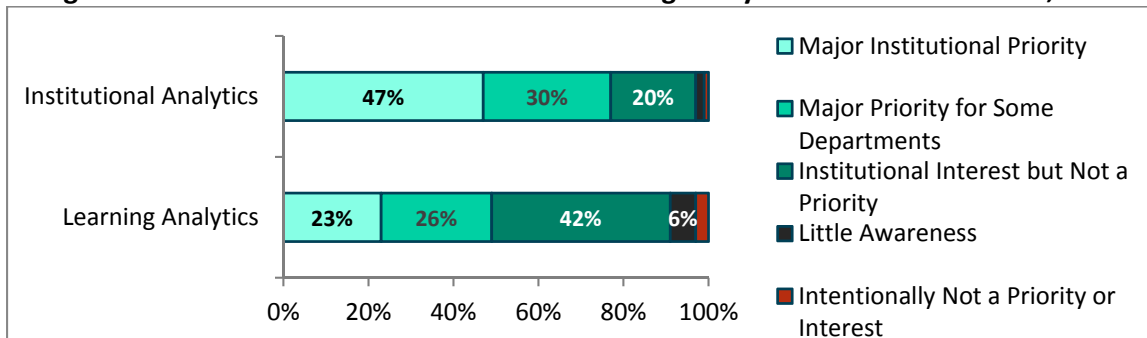
Source: EDUCAUSE[9]

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[6] Clow, D. "The Learning Analytics Cycle: Closing the Loop Effectively." *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, New York: ACM, 2012. LAK '12. pp. 134–135. http://oro.open.ac.uk/34330/1/LAK12-DougClow-personalcopy.pdf

[7] Long, P. and G. Siemens. "Penetrating the Fog: Analytics in Learning and Education." Educause Review, 2011. p. 34. https://net.educause.edu/ir/library/pdf/ERM1151.pdf

[8] Arroway, P. et al. "Learning Analytics in Higher Education." Educause. p. 8. https://library.educause.edu/~/media/files/library/2016/2/ers1504la.pdf

[9] "Analytics Landscape: A Comparison of Institutional and Learning Analytics in Higher Education." Educause, April 22, 2016. https://library.educause.edu/~/media/files/library/2016/4/eig1504.pdf

Among U.S. higher education institutions, learning analytics initiatives are commonly connected to student performance monitoring, specifically related to improved retention, subject completion, and reduced time-to-degree initiatives.[10] Similarly in Australia, student retention is the primary driver for new or improved LA implementations.[11] Attrition rates continue to increase, with approximately one in five bachelor's students diverting from their original course of study and 15 percent dropping out entirely.[12]

The type and level of analysis varies, both for learning analytics and institutional analytics. Figure 1.3 lists several common implementations referenced in literature and case studies, identified by major category (learning vs. institutional) and the level of analysis.

Figure 1.3: Examples of Learning and Institutional Analytics Employed in Higher Education

ANALYTICS CATEGORY	LEVEL OF ANALYSIS	TYPE OF ANALYSIS
Learning Analytics	Course Level	▪ Social Network Analysis ▪ Conceptual Development Analysis ▪ Discourse Analysis ▪ Personalized Curriculum ▪ Student Performance Assessment
	Student Level	▪ Degree Audit ▪ Performance Assessment ▪ Predictive Performance Analysis/Early Warning Systems ▪ Automated Advising and Coaching
	Departmental Level	▪ Early Warning/Predictive Modelling
Institutional Analytics	Instructor Level	▪ Teacher Effectiveness ▪ Financial Contributions
	Student or Student Body Level	▪ Enrolment Profiling and Predictive Analysis ▪ Lifetime Value/Booster Effectiveness ▪ Advocacy ▪ Post-Educational Employment Analysis ▪ Subject or Course Selection Recommendations
	Institutional Level	▪ Admissions Analysis ▪ Institutional Performance/Efficiency ▪ Retention/Attrition Trends
	Public Level	▪ Comparison with Other Institutions

Source: Arroway,[13] Clow[14], IBM,[15] U.S. Department of Education[16]

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[10] Arroway et al., Op. cit., p. 5.

[11] Colvin, C. et al. "Student Retention and Learning Analytics: A Snapshot of Australian Practices and a Framework for Advancement." Australian Government Office for Learning and Teaching, 2016. p. 14. http://he-analytics.com/wp-content/uploads/SP13_3249_Dawson_Report_2016-3.pdf

[12] Burke, L. "University Attrition Rates: Why Are so Many Students Dropping Out?" NewsComAu, September 8, 2016. http://www.news.com.au/finance/work/careers/university-attrition-rates-why-are-so-many-students-dropping-out/news-story/3e491dd119e1249a5a3763ef8010f8b5

[13] Arroway et al., Op. cit.

COMMON METRICS AND DATA SOURCES

Institutions collect a wide variety of data for institutional and learning analytics, some of which are summarized in Figure 1.4. For efforts related to student success, the majority of data is derived from two sources:[17]

- The **learning management system (LMS)** or **virtual learning environment (VLE)**, as these systems already collect data from students as they complete assignments, access materials, take quizzes and exams, or interact with fellow students and professors
- **Student information systems** within the institution that log information, such as enrolment data, transcripts, and demographics.

Figure 1.4: Common Metrics for Student Success Analytics

CATEGORY	METRIC(S)	DATA SOURCE(S)
Student Activity/ Engagement	- System access/session data - Usage or interaction data (for specific tools or items) - Conversational data - Social network data	LMS, Other institutional system (e.g., library or writing center)
Student Progress/ Competency	- Assignment or test completion - Assignment or test grades - Task performance - Positive behaviors - Conversational data	LMS, Instructor report
Academic History	- Secondary education GPA - Standardized testing scores - Academic preparation	Student transcripts
Student Characteristics	- Demographics - Degree/course enrolment - Financial aid status	Enrolment data, Student transcripts
Student Perceptions	- Emotional state - Attitudes toward subject or course - Level of self-confidence	Self-report/survey

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[14] Clow, "An Overview of Learning Analytics," Op. cit.

[15] Schmarzo, B. "What Universities Can Learn from Big Data – Higher Education Analytics." InFocus Blog | Dell EMC Services, July 2, 2014. https://infocus.emc.com/william_schmarzo/what-universities-can-learn-from-big-data-higher-education-analytics/

[16] Bienkowski, M., M. Feng, and B. Means. "Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics: An Issue Brief." U.S. Department of Education, October 2012. http://tech.ed.gov/wp-content/uploads/2014/03/edm-la-brief.pdf

[17] "Learning Analytics in Higher Education." Jisc. https://www.jisc.ac.uk/reports/learning-analytics-in-higher-education

CATEGORY	METRIC(S)	DATA SOURCE(S)
Student Plans	▪ Curriculum or subject plan ▪ Study plans for subject ▪ Desired grade or graduation level	Self-report/survey

Source: Jisc[18]

PLATFORMS AND TOOLS

Reviewed case studies and literature identify several software tools, services, and platforms that higher education institutions may use to collect, manage, and display data used for learning analytics initiatives. Figure 1.5 lists several prominent examples.

Figure 1.5: Tools and Platforms for Learning Analytics

CATEGORY	TOOL OR PLATFORM*
LMS System or Extension	▪ Blackboard Intelligence ▪ Brightspace Insights ▪ Moodle analytics plugins ▪ Social Network Analysis and Pedagogical Practices (SNAPP) for Sakai ▪ SmartKlass LMS/VLE Plugin ▪ Kaltura video plugin for LMS/VLE, with analytics
Data Visualization	▪ HighCharts ▪ Tableau
Analytics Platforms	▪ Civitas Learning Student Insights Engine ▪ SEAtS Learning Analytics

*Each tool or platform name includes a hyperlink to the platform home page.

CONCERNS AND CRITICISM

Students, parents, and university personnel have raised some concerns regarding learning analytics. **The majority of these concerns relate to maintaining student privacy amidst the increased collection of data.** The development and proliferation of analytics technology has passed the sophistication of the regulatory environment, leaving educational data mining and analytics in uncharted territory.[19]

While many students appear unconcerned with sharing personal information online, students may not be fully aware of the amount or types of data that universities collect as part of their analytics. For example, when the Open University began developing a policy regarding ethical use of student data for analytics, it consulted with 60 students about learning analytics. The University found that the majority of students were unaware of the

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[18] Ibid.

[19] Manai, J. "The Learning Analytics Landscape: Tension Between Student Privacy and the Process of Data Mining." Carnegie Foundation for the Advancement of Teaching, November 6, 2015. https://www.carnegiefoundation.org/blog/the-learning-analytics-landscape-tension-between-student-privacy-and-the-process-of-data-mining/

capabilities for data collection and analytics. Some students, upon learning of the practice, were unconcerned, but many expressed discomfort with analyses performed on them individually, likening it to "snooping."[20]

While consent for data gathering can be implemented, a review by the U.S. government questioned whether "notice and consent" models allow meaningful control when data are used repeatedly, including in ways that may not have been anticipated during collection.[21] Consent for disclosure can be difficult as well, as disclosure may be challenging to anticipate when data are combined and processed in certain ways. For complex and predictive analysis, "the more features of the data that are released (e.g., time of day homework was done simultaneously) the more valuable predictions can be (e.g., hours of operation for school-based homework centers) and the higher the likelihood of unintended disclosure (e.g., by pinpointing students who work after school)."[22]

In addition to the prevalent privacy issue, **some institutional personnel voice concerns about technology and service vendors** who "operate without the ethical obligations to students that institutions have, and design their products at a remove from the spaces where learning happens."[23] Data stored with third-party services or processed by algorithms designed by these vendors could be at additional risk, and institutions may want to ensure a degree of control and transparency over services and models developed/provided by industry.

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[20] [1] "Ethical Use of Student Data for Learning Analytics Policy." The Open University, 2014.
http://www.open.ac.uk/students/charter/essential-documents/ethical-use-student-data-learning-analytics-policy
[2] Parr, C. "Lecturer Calls for Clarity in Use of Learning Analytics." Times Higher Education (THE), November 6, 2014. https://www.timeshighereducation.com/news/lecturer-calls-for-clarity-in-use-of-learning-analytics/2016776.article

[21] Podesta, J. "Findings of the Big Data and Privacy Working Group Review." The White House, May 1, 2014.
https://www.whitehouse.gov/blog/2014/05/01/findings-big-data-and-privacy-working-group-review

[22] Bienkowski, Feng, and Means, Op. cit., p. 42.

[23] Brown, J. "Leading the Way in Learning Analytics." Ithaka S+R, September 9, 2016.
http://www.sr.ithaka.org/blog/leading-the-way-in-learning-analytics/

SECTION II: CASE STUDIES FOR STUDENT-FACING ANALYTICS

In this section, Hanover provides several examples of learning analytics for student success at higher education institutions. Specific uses of analytics in the following case studies include early warning/at-risk identification systems for student retention, student progress tracking dashboards, and course selection recommendations.

PEER POSITIONING: UNIVERSITY OF MARYLAND BALTIMORE COUNTY'S "CHECK MY ACTIVITY"

When it examined its learning management system (LMS) usage data, the University of Maryland Baltimore County (UMBC) discovered that students earning below a C continually demonstrated 40 percent lower usage of the LMS compared to students earning a C or better.[24] As such, it was possible that overall LMS usage data could provide an ongoing formative assessment of student performance within the subject. In keeping with institutional priorities that students must be responsible for their own learning, UMBC decided to share LMS usage data with students.

UMBC launched the **Check My Activity (CMA)** feedback tool in 2008 to provide students with information about their own performance within the LMS system. The CMA is built into the Blackboard LMS system used by the University, and students access it through links in the LMS header or in each subject.[25] CMA collects two key pieces of information:

- **Sessions:** Number of times the student logged into the particular Blackboard subject
- **Hits**: Discrete interactions within the subject (e.g., viewing a file or posting to the discussion board)

To contextualize this information, CMA allows students to compare their activity against a summary of anonymized peer data. At a high level, students can see an overview of their activity across all Blackboard subjects compared to the overall class average (see Figure 2.1). If the instructor uses the gradebook function within a subject, CMA allows the student to compare their own activity against the anonymized average activity of students who earned equivalent, lower, and higher grades on any assignment (see Figure 2.2).[26] For online subjects, where students may not interact regularly with their peers or opportunities to discuss course content or performance, aggregated and anonymized peer reports may be particularly helpful.

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[24] Fritz, J. "Using Analytics at UMBC: Encouraging Student Responsibility and Identifying Effective Course Designs." Educause, April 30, 2013. p. 1. https://net.educause.edu/ir/library/pdf/ERB1304.pdf

[25] Fritz, J. "Video Demo of UMBC's 'Check My Activity' Tool for Students." Educause Review, December 15, 2010. http://er.educause.edu/articles/2010/12/video-demo-of-umbcs-check-my-activity-tool-for-students
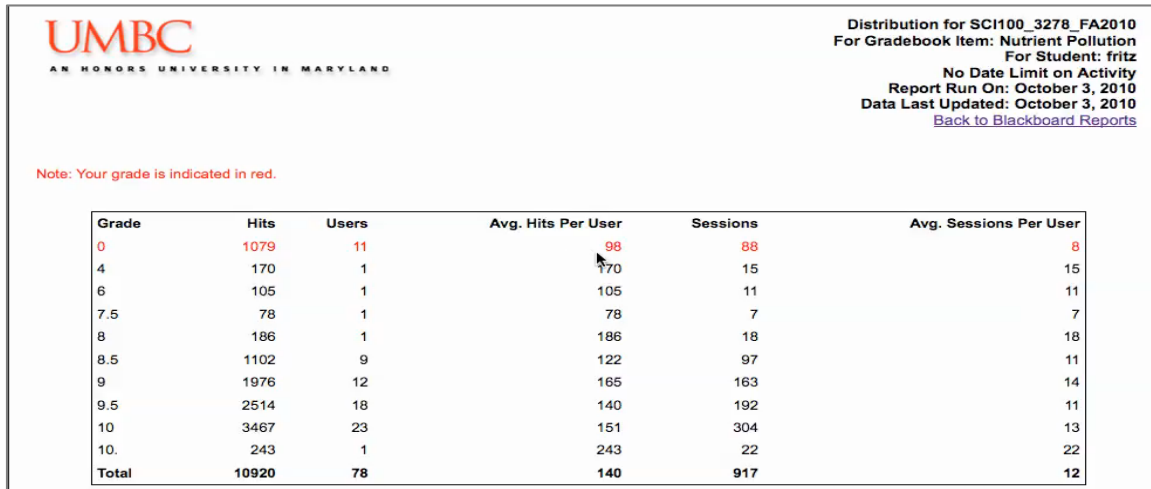
[26] Fritz, "Using Analytics at UMBC: Encouraging Student Responsibility and Identifying Effective Course Designs," Op. cit., p. 2.

Figure 2.1: CMA Activity Summary*
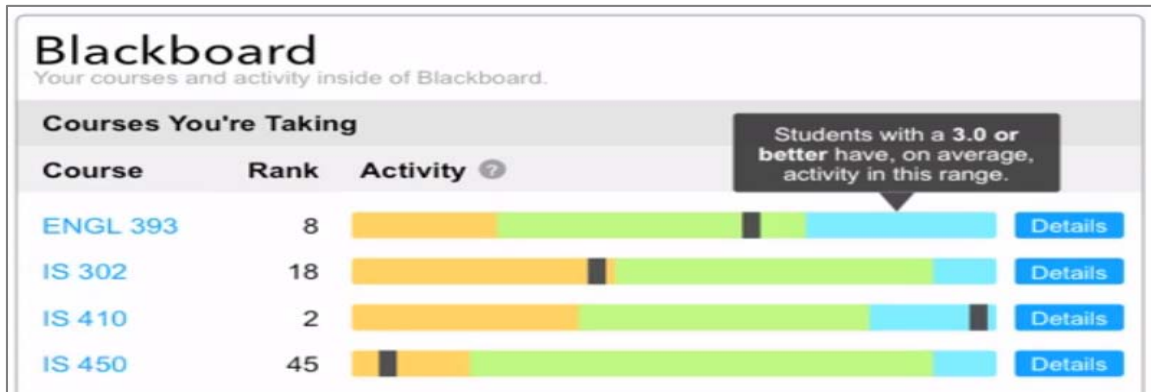
Source: UMBC[27]

Figure 2.2: CMA Peer Comparison Data for a Single Assignment

Source: Fritz[28]

Figure 2.3: Proposed Peer Comparison Report Format for CMA*
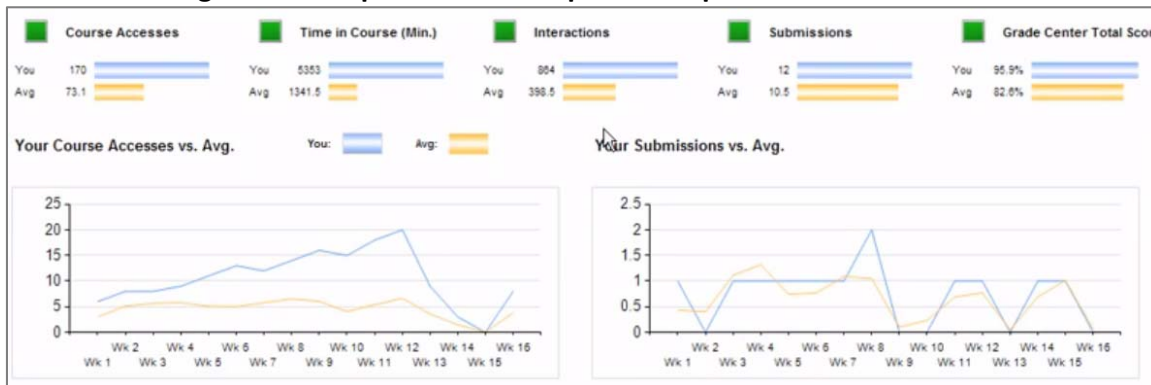
Source: UMBC[29]

*Note: These interfaces are prototypes, and it is unclear whether they have been officially rolled out at UMBC.

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[27] "SP2013 UMBC Analytics Preview." YouTube. https://www.youtube.com/watch?v=iLifdZ5sRMc&feature=youtu.be
[28] Fritz, "Video Demo of UMBC's 'Check My Activity' Tool for Students," Op. cit.
[29] "SP2013 UMBC Analytics Preview," Op. cit.

Outcomes data from CMA is still in the early stages. However, initial reports suggest that the tool may have an impact on raising student self-awareness regarding their performance. Student surveys from one subject showed that 28 percent of students were surprised by the data, while another 12 percent reported that it confirmed their existing understanding of their own performance. However, nearly half (42 percent) were unsure and thought they needed more experience with the tool. Figure 2.4 shows the full range of responses.

Figure 2.4: Response to CMA Dashboard Information
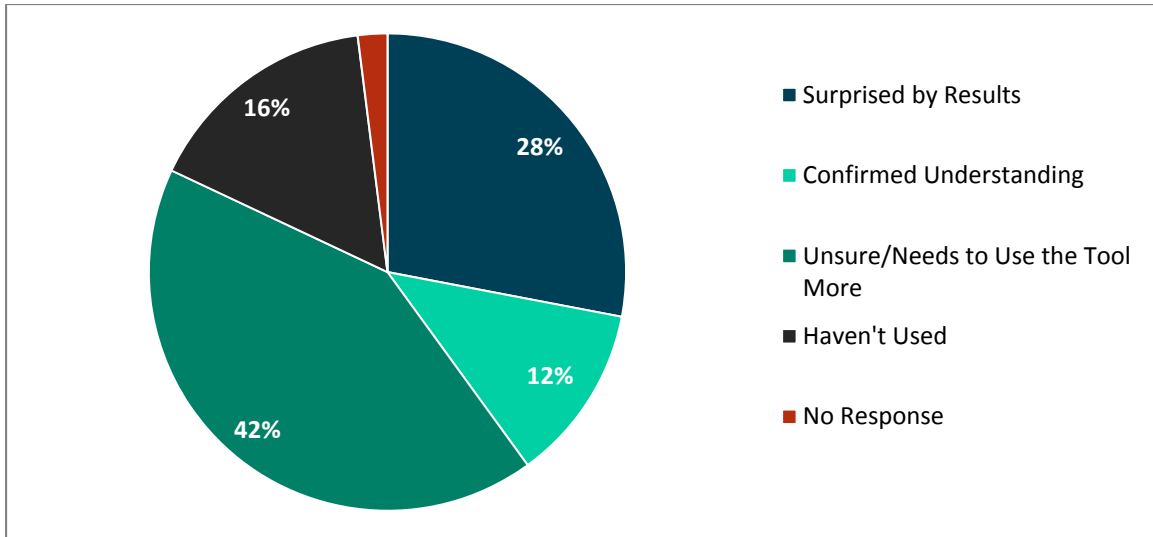
Source: Fritz[30]

Students who use the tool once tend to use it again in the future. The same subject survey reported that more than half (54 percent) of the class would be more likely to use CMA before future assignments.[31] The response to CMA has also impacted curriculum design choices at UMBC, spurring an increase in the number of instructors using the gradebook functionality and incorporating more interactive aspects within their Blackboard subjects. Gradebook usage increased from less than half (46 percent) in 2006 to 60 percent in 2012.[32]

AT-RISK WARNINGS FOR STUDENTS & INSTRUCTORS: PURDUE'S "COURSE SIGNALS"

Student attrition has been identified as an ongoing issue in higher education, and learning analytics can play a central role in retention efforts. To provide pre-emptive support to students who may be at academic risk, **Purdue University** launched an analytics system and dashboard called **Course Signals**. Course Signals uses data gathered from the Blackboard LMS in conjunction with predictive algorithms based on prior patterns observed for students who struggle in subjects to anticipate whether a student may need extra support.

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[30] Fritz, "Video Demo of UMBC's 'Check My Activity' Tool for Students," Op. cit.
[31] Ibid.
[32] Fritz, "Using Analytics at UMBC: Encouraging Student Responsibility and Identifying Effective Course Designs," Op. cit., p. 4.

Course Signals is run manually by the instructor as many times during the semester as they wish, and the instructor updates the at-risk status of all enrolled students accordingly.[33] At a broad level, there are **four major metrics components: subject performance, effort, prior history,** and **student characteristics.** Figure 2.5 provides examples of the types of specific data incorporated into each category.

Figure 2.5: Metrics Categories and Selected Examples Used in Course Signals

Performance	Effort	Prior Academic History	Student Characteristics
•Points earned to date	•Interaction with LMS (compared to peers)	•Academic preparation •High school GPA •Standardised test scores	•Residency •Age •Credits attempted

Source: Arnold and Pistilli[34]

Some aspects, such as earned points, are based on thresholds set by the instructor for that particular subject. For example, some instructors may consider 81 percent and above to be low risk, while others might place the bottom of the threshold at 90 percent.[35] The high, medium, and low risk categories are displayed to the student via a traffic signal visualization of red/yellow/green lights (Figure 2.6).

Figure 2.6: Signals Overview Page
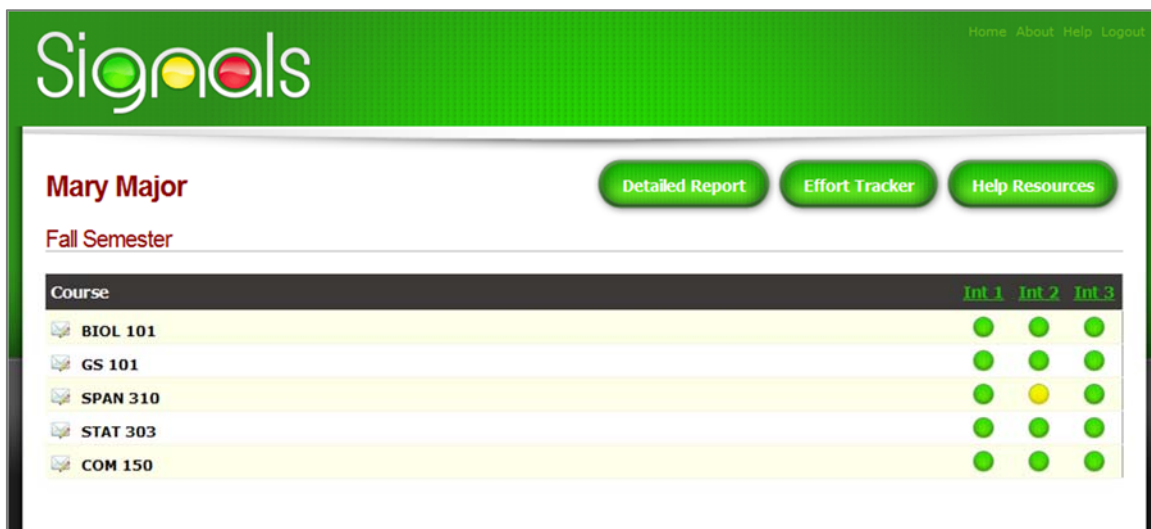
Source: Purdue University[36]

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[33] Pistilli, M.D., K. Arnold, and M. Bethune. "Signals: Using Academic Analytics to Promote Student Success." Educause, July 17, 2012. http://er.educause.edu/articles/2012/7/signals-using-academic-analytics-to-promote-student-success

[34] Arnold, K.E. and M.D. Pistilli. "Course Signals at Purdue: Using Learning Analytics to Increase Student Success." ACM Press, 2012. pp. 1–2. http://dl.acm.org/citation.cfm?doid=2330601.2330666

[35] Pistilli, Arnold, and Bethune, Op. cit.

[36] "Signals at Purdue University." Purdue University. http://www.itap.purdue.edu/studio/signals/

Students identified as "at risk" receive follow-up interventions including both automated and manual email messages from instructors, referrals to advising services or resource centers, and scheduling for face-to-face meetings with instructors.[37] In addition to help provided from the instructor or institution to the student, Course Signals improves students' own awareness of their performance and may prompt them to reach out for support proactively. Tim Delworth, a mathematics lecturer at Purdue, reported, "Before, no one would e-mail me and say, 'I'm at 58 percent and I want to get to 72 percent, what do I need to do?' But the students who get a red light almost all contact me immediately to ask how to raise their grades."[38] Student reported feedback has also been positive, with 89 percent stating that Course Signals was a positive experience and 74 percent reporting that Course Signals improved their motivation.[39]

While Course Signals has experienced a great deal of positive publicity and reported strong results, there has been some criticism and controversy regarding the validity of the system's data and reported results, specifically regarding improved retention. Purdue has reported positive results from the use of Course Signals.[40] However, Michael Caulfield, director of blended and networked learning at Washington State University, has suggested that the publicized data exhibits a potential reverse causality problem. Caulfield hypothesized that "rather than students taking more CS-courses retaining at a higher rate, what was really happening was that the students who dropped out mid-year were taking less CS classes because they were taking less classes period. In other words, the retention/CS link existed, but not in a meaningful way."[41] The head of analytics at McGraw-Hill conducted a simulation that seems to confirm Caulfield's theory.[42]

Regardless of the actual effectiveness of Course Signals, this criticism raises relevant questions about metrics considered and results reported within the analytics community. The metrics directly used in analytics, as well as outcomes derived from learning analytics, must be carefully considered and positioned in an appropriate context with other variables to yield accurate and usable results. As McGraw-Hill's head of analytics states:[43]

> Maybe one of the conclusions that could be derived from this is that we really don't have a strong community to test and validate these claims? Maybe that's really the starting point of discussion in the academic community. As we move forward with new technologies in learning analytics, how and who will be evaluating the claims that people put forward?

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[37] Arnold and Pistilli, Op. cit., p. 2.

[38] Tally, S. "Signals Tells Students How They're Doing Even before the Test." Purdue University, September 1, 2009. http://www.purdue.edu/uns/x/2009b/090827ArnoldSignals.html

[39] Arnold and Pistilli, Op. cit., p. 3.

[40] Ibid.

[41] Caulfield, M. "What the Course Signals 'Kerfuffle' is About, and What It Means to You." Educause Review, November 13, 2013. http://er.educause.edu/blogs/2013/11/what-the-course-signals-kerfuffle-is-about-and-what-it-means-to-you

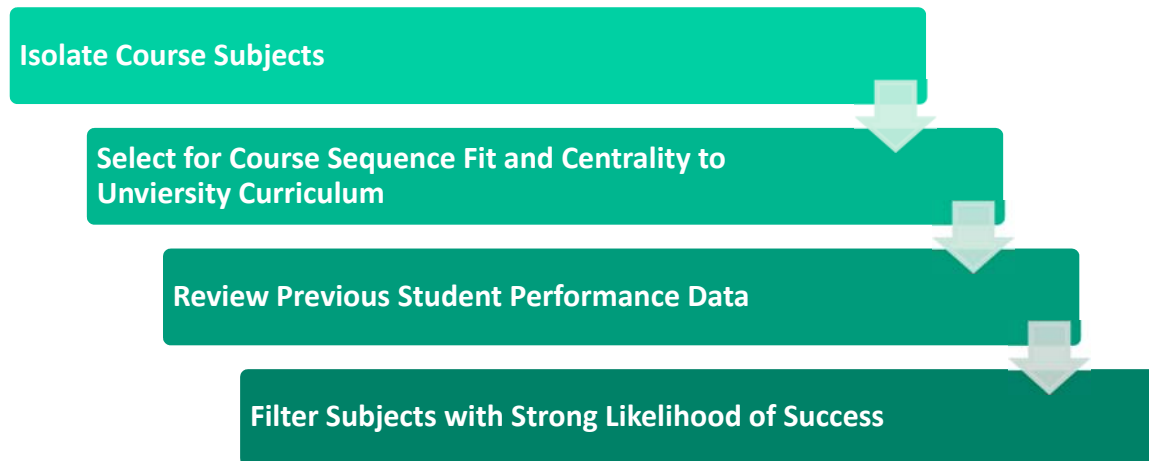[42] Essa, A. "Can We Improve Retention Rates by Giving Students Chocolates?" Alfredessa.com, October 14, 2013. http://alfredessa.com/2013/10/can-we-improve-retention-rates-by-giving-students-chocolates/

[43] Straumsheim, C. "Student Retention Software Comes under Microscope." Times Higher Education (THE), November 11, 2013. https://www.timeshighereducation.com/news/student-retention-software-comes-under-microscope/2008904.article

TAILORED SUBJECT RECOMMENDATIONS: AUSTIN PEAY'S "DEGREE COMPASS" AND "MY FUTURE"

Recommendation systems, such as product or movie recommendations through services like Amazon or Netflix, are one common business analytics application. Inspired by these systems, **Austin Peay State University** developed **Degree Compass**, a subject recommendation system that "pairs current students with the courses that best fit their talents and program of study for upcoming semesters."[44] Austin Peay's provost hopes the system will help make students aware of subjects they might not otherwise consider and help students to avoid subjects for which they are not prepared.[45]

The full range of metrics and the predictive algorithms have not been publicly disclosed. However, Austin Peay's website explains that the system performs the following steps:[46]

Isolate Course Subjects

Select for Course Sequence Fit and Centrality to Unviersity Curriculum

Review Previous Student Performance Data

Filter Subjects with Strong Likelihood of Success

Austin Peay reports that the Degree Compass algorithm successfully predicts student grades in recommended subjects in more than 90 percent of subjects, and with relatively high accuracy (within 0.6 of a letter grade on average).[47] Overall comparisons of student grades before and after the introduction of Degree Compass "show a steadily increasing proportion of ABC grades so that results in fall 2012 are almost 5 standard deviations better than those in fall 2010."[48]

Due to positive reception and results from Degree Compass, Austin Peay has instituted a similar recommendations program, **"My Future,"** which assists students with courses. Students who have already selected a field of study receive additional information on

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[44] "Degree Compass - What Is It?" Austin Peay State University. http://www.apsu.edu/information-technology/degree-compass-what

[45] Young, J.R. "The Netflix Effect: When Software Suggests Students' Courses." *The Chronicle of Higher Education*, April 10, 2011. http://www.chronicle.com/article/The-Netflix-Effect-When/127059/

[46] "Degree Compass - What Is It?" Op. cit.

[47] "Degree Compass and My Future." Austin Peay State University. http://www.apsu.edu/academic-affairs/degree-compass-and-my-future

[48] Ibid.

concentrations and degree paths, as well as career information such as links to U.S. Department of Labor statistics for relevant occupations and job availability. Students without a selected field of study, or who are considering a different field, can retrieve suggestions for various fields in which the student is likely to succeed, much like the predictive subject performance ratings in Degree Compass.[49]

ACTIVITY, PERFORMANCE, & FEELINGS INTEGRATION: UNE'S EARLY ALERT SYSTEM

Like other institutions discussed in this report, the University of New England (UNE) student retention is a concern at the University of New England. To address student attrition, UNE implemented an early alert system to identify students at risk of attrition. UNE's system incorporates subjective and emotional data into its early warning analytics, a relatively unique approach.

Over time, the system has incorporated several major components:

- **E-Motion** captures student emotional states in relation to their subject by providing a self-reporting interface that uses emoticons as well as a free-response text box. Students select an emoticon that represents their current feelings about the subject, ranging from happy to very unhappy.[50] UNE's Student Support Team contacts any students who record a negative emotion ("unhappy" or "very unhappy") within 24 hours.[51]

- **The Vibe** displays data self-reported by students in the text field next to the emoticon selection. The field accepts a total of 140 text characters, equivalent to a Twitter post.[52] Every 10 minutes, text box comments are processed and repeated key words are counted. The Vibe then displays a word cloud of the key student-supplied terms, with more frequently reported words appearing in a larger font size.[53] Unlike the other data, The Vibe is available to students to communicate a general understanding of how their peers are feeling. When terms reported or felt by the student are emphasized within the word cloud, students' feelings of isolation may be mitigated.[54]

- The **Automated Wellness Engine (AWE)**, implemented in the second and third stages of the early alert system, analyses student data from multiple different systems each evening. The following morning, the system updates the Student Support Team dashboard with an identification of students who need assistance.[55]

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[49] Ibid.

[50] "Learning Analytics in Higher Education," Op. cit.

[51] [1] Leece, R. and E. Campbell. "Engaging Students through Social Media." *Journal of the Australia and New Zealand Student Services Association*, :38, October 2011. p. 11. [2] "Learning Analytics in Higher Education," Op. cit.

[52] Leece and Campbell, Op. cit., p. 12.

[53] "Learning Analytics in Higher Education," Op. cit.

[54] Leece and Campbell, Op. cit., p. 12.

[55] "Learning Analytics in Higher Education," Op. cit.

Figure 2.7: E-Motion Self-Reporting Interface

Source: Leece and Cooper[56]

AWE incorporates several sets of behavioral data, including the e-Motion and Vibe data, class attendance, prior study history, assignment submissions, university system access data (e.g., LMS or library usage), and prior AWE score history. Certain data points, or "triggers," are more heavily weighted than others. The highest weight is granted to student e-Motion negative self-reports, going more than 40 days without accessing the student portal, or not completing a unit during a prior semester. [57]

Student attrition rates reduced from 18 percent to 12 percent during initial trials for AWE, and student feedback has been largely positive, indicating an increased sense of community and improved motivation.[58]

SUBJECT PROGRESS MONITORING: RIO SALADO COLLEGE'S "RIOPACE"

Rio Salado College, a two-year institution in Arizona, implemented a subject progress tracking system for students called Rio Progress and Course Engagement (PACE). The system calculates the student's current performance within the subject and assigns it to a low, medium, or high level of risk for subject completion. Similar to Purdue's Course Signals, RioPACE displays color-coded icons (green, yellow, and red) on the student's LMS site and beside the student's name within the instructor's interface.[59]
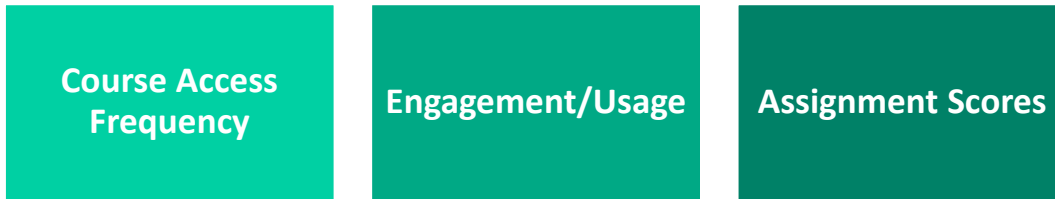
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[56] Leece, R. and J. Cooper. "Automated Student Wellness Engine - Proactively Managing Student Wellbeing at UNE." Prezi, 2011. https://prezi.com/m5qui5cptvay/copy-of-unes-automated-student-wellness-engine/
[57] "Learning Analytics in Higher Education," Op. cit.
[58] Leece and Campbell, Op. cit., pp. 12–13. [2] "Learning Analytics in Higher Education," Op. cit.
[59] [1] Grush, M. "Monitoring the PACE of Student Learning: Analytics at Rio Salado College -." Campus Technology, December 14, 2011. https://campustechnology.com/articles/2011/12/14/monitoring-the-pace-of-student-

RioPACE considers three main categories of metrics:[60]

| Course Access Frequency | Engagement/Usage | Assignment Scores |

Students can view a tooltip for their current RioPACE rating, which displays their status on each of these three categories (Figure 2.8).

Figure 2.8: RioPACE Status Display
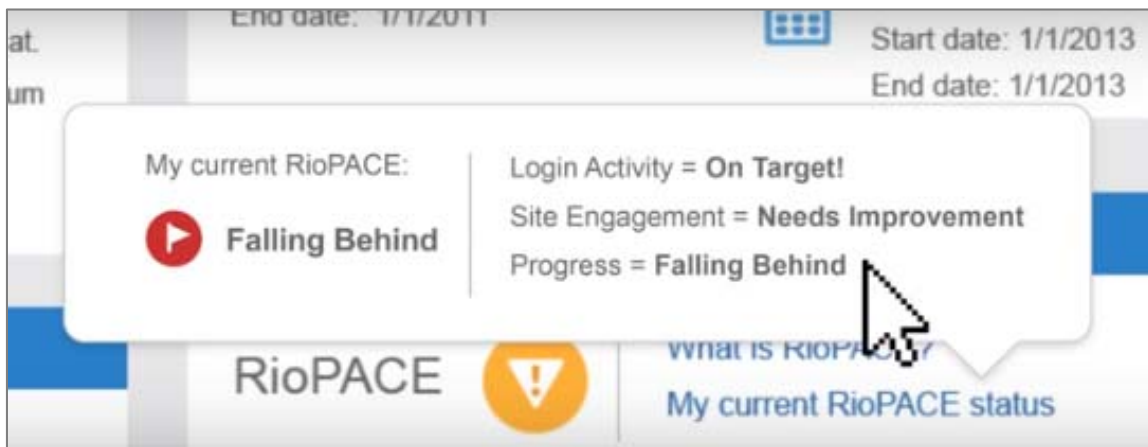
Source: Rio Salado College[61]

PERSONALISED COACHING & GAMIFIED STATUS TRACKING: ANALYTICS AT THE UNIVERSITY OF MICHIGAN

E^2COACH FEEDBACK AND ADVISING SYSTEM

As a big university, the University of Michigan has a number of large introductory subjects, sometimes consisting of more than 500 students in a single lecture group.[62] As such, professors face difficulty keeping track of and providing advice to all students during their initial postsecondary experience. To address this challenge, a research team at the University developed **E^2Coach** to provide tailored support communications related to student progress.

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learning-analytics-at-rio-salado-college.aspx [2] "RioPACE." Rio Salado College. http://www.riosalado.edu/riolearn/Pages/RioPACE.aspx

[60] Grush, Op. cit.

[61] "RioPACE," Op. cit.

[62] Huberth, M., N. Michelotti, and T. McKay. "E2Coach: Tailoring Support for Students in Introductory STEM Courses." Educause Review, December 6, 2013. http://er.educause.edu/articles/2013/12/e2coach-tailoring-support-for-students-in-introductory-stem-courses

Students using the system "receive personalized assistance in large classes, learn best practices, discover opportunities in areas of interest, and avoid common pitfalls."[63] Feedback messages are crafted in template form by a message author and designed to contain specific variable spaces where personalized information can be inserted for each individual student. **Student data derives from a detailed survey** that collects several types of information, including:[64]

- Name and major
- Levels of preparation for the subject
- Attitudes about science
- Study plans
- Desired grade
- Level of confidence in their ability to obtain the desired grade

Students also receive advisory messages with congratulations, motivational tips, or performance improvement recommendations submitted by prior students for use as peer coaching. E[2]Coach compares the student's demographics with those of the students in the advisory comment database and pulls comments specifically from peers (i.e., those that match the student in gender and course).[65]

In addition to the tailored advising messages, students can also view personalized, comparative graphics about their status in the subject. Figure 2.9 on the following page provides an example of several charts available to students within the system. UM uses the **HighCharts** graphic library, a free, non-commercial resource, to generate graphics in response to specific student questions like "how am I doing in relation to classmates?" or "what grade am I currently on track to receive?" For some of these questions, E[2]Coach uses prior assignment data from the subject or historical data from prior semesters to display information such as average number of hours that prior students planned to devote to homework.[66]

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[63] "ECoach: Personalized Messaging to Students." University of Michigan Academic Innovation. http://ai.umich.edu/portfolio/e-coach/
[64] Adapted from: Huberth, Michelotti, and McKay, Op. cit.
[65] educause. "E2Coach EDUCAUSE." YouTube, October 22, 2013. https://www.youtube.com/watch?time_continue=1&v=3liHgIvYKuM
[66] Huberth, Michelotti, and McKay, Op. cit.

Figure 2.9: On-Demand Performance Feedback Graphics from E²Coach
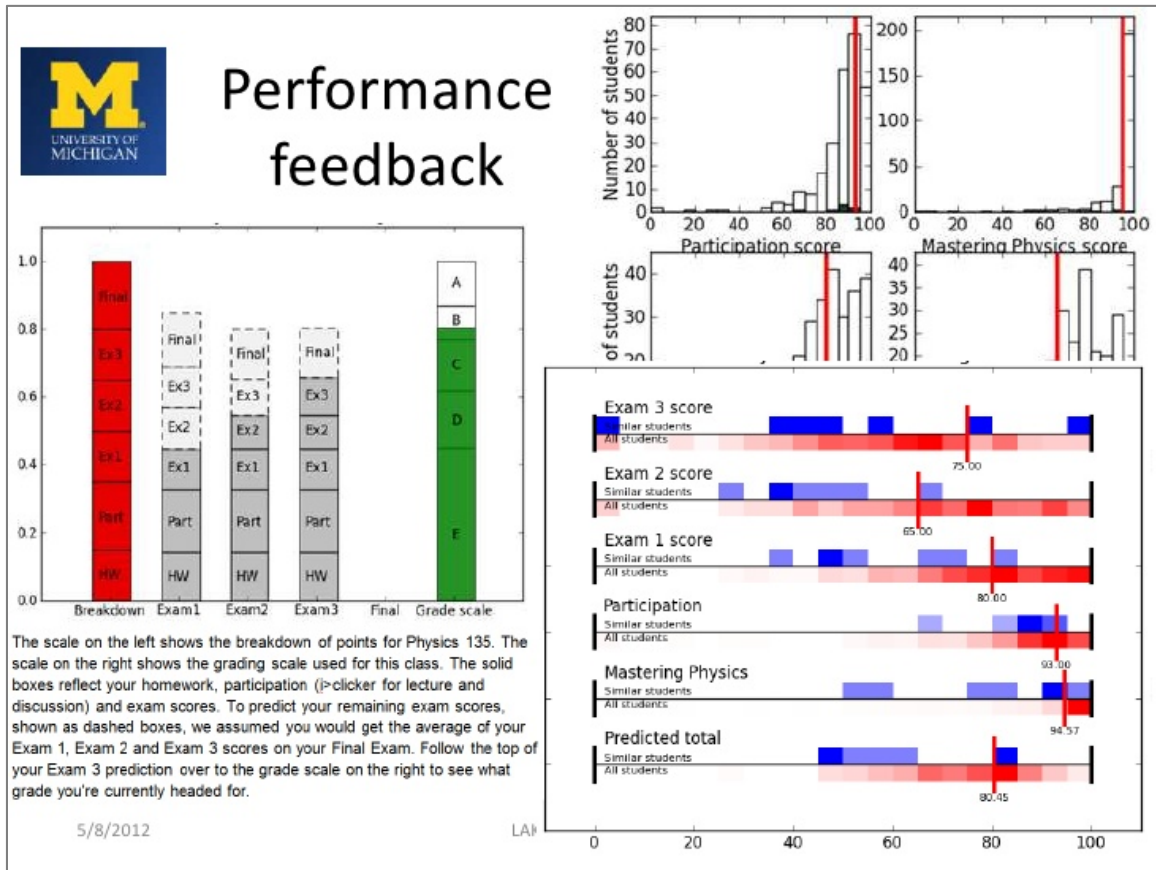
Source: McKay[67]

GRADECRAFT GAMIFIED LMS

To stimulate learner engagement, UM developed a game-inspired system that implements points and levels, badges, retries for assignments, and selection of assignments.[68] These subjects incorporate a large number of features and metrics for students to track. Therefore, UM developed a gamified gradebook, **GradeCraft**, which was later expanded into a full LMS.[69] As an LMS, GradeCraft provides visualizations and information to both students and instructors.

The student dashboard in GradeCraft displays "their current score, a chart of the points they have earned so far in the course, and a chart of the points that are available to earn

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[67] McKay, T. "What to Do with Actionable Intelligence: E2Coach as an Intervention Engine." Presentation presented at the 2nd International Conference on Learning Analytics and Knowledge, 2012. http://www.slideshare.net/tamckay/lak12-e2coach-presentation
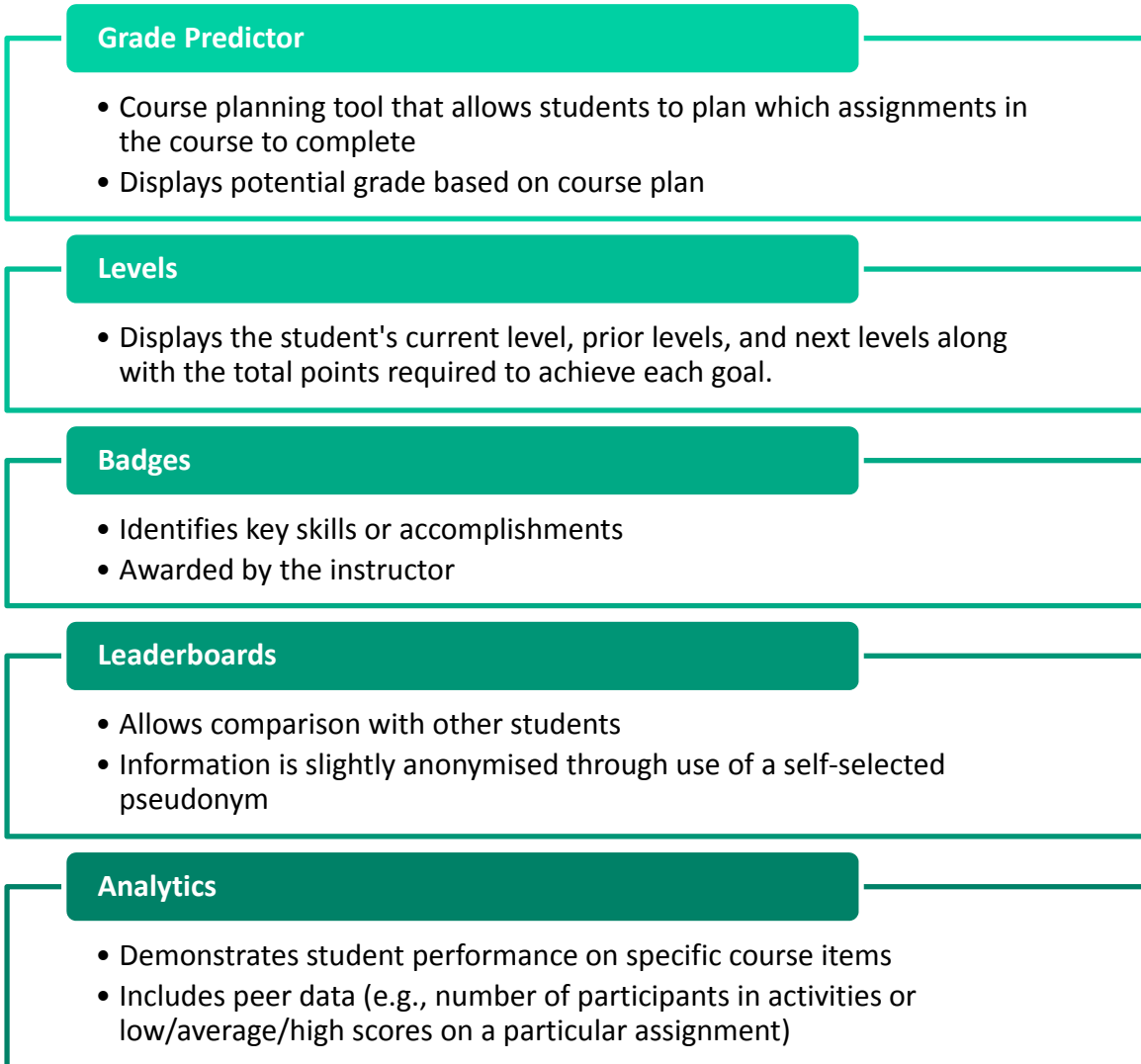
[68] Holman, C., S. Aguilar, and B. Fishman. "GradeCraft: What Can We Learn From a Game-Inspired Learning Management System?" *Proceedings of the Third International Conference on Learning Analytics and Knowledge*, presented at the LAK13, ACM, 2013. p. 260. https://www.gradecraft.com/research/LAK2013-GradeCraft-Design_Briefing.pdf

[69] Ibid.

throughout the entire course."[70] Figure 2.10 describes the different components of GradeCraft, and Figure 2.11 on the following page provides a sample screenshot.

Figure 2.10: Dashboard Segments Provided in GradeCraft

Grade Predictor

- Course planning tool that allows students to plan which assignments in the course to complete
- Displays potential grade based on course plan

Levels

- Displays the student's current level, prior levels, and next levels along with the total points required to achieve each goal.

Badges

- Identifies key skills or accomplishments
- Awarded by the instructor

Leaderboards

- Allows comparison with other students
- Information is slightly anonymised through use of a self-selected pseudonym

Analytics

- Demonstrates student performance on specific course items
- Includes peer data (e.g., number of participants in activities or low/average/high scores on a particular assignment)

Source: GradeCraft[71]

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[70] Ibid., p. 261.
[71] "Features." GradeCraft. https://www.gradecraft.com/features

Figure 2.11: Level Display and Comparative Analytics Example

Source: GradeCraft[72]

COMPETENCY TRACKING: CAPELLA UNIVERSITY'S COMPETENCY MAP

Capella University has been investing in competency-based education models. Three years ago the institution even began implementing entirely competency-based courses without formal subject structures or credit hours. Instead, it uses "direct assessment" based on assignment completion and demonstration of skills.[73]

To help students track their progress, Capella instituted the **Competency Map** interface, a dashboard containing the current competencies and assignments required by the subject or course, along with the portion of these that the student has completed, shown in Figure 2.12. Competency graphs are color-coded to denote the degree of competency. This format gives learners "a concise overview of what is expected of them, and how much progress they have achieved."[74]

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[72] Ibid.

[73] Fain, P. "Competency-Based Education's Newest Form Creates Promise and Questions." Inside Higher Ed, April 22, 2013. https://www.insidehighered.com/news/2013/04/22/competency-based-educations-newest-form-creates-promise-and-questions

[74] Reimers, G. and A. Neovesky. "Student Focused Dashboards – An Analysis of Current Student Dashboards and What Students Really Want." *7th International Conference on Computer Supported Education*, 2015. p. 401. http://www.academia.edu/12885290/Student_Focused_Dashboards_An_Analysis_of_Current_Student_Dashboards_and_What_Students_Really_Want

Figure 2.12: Competency Map Dashboard
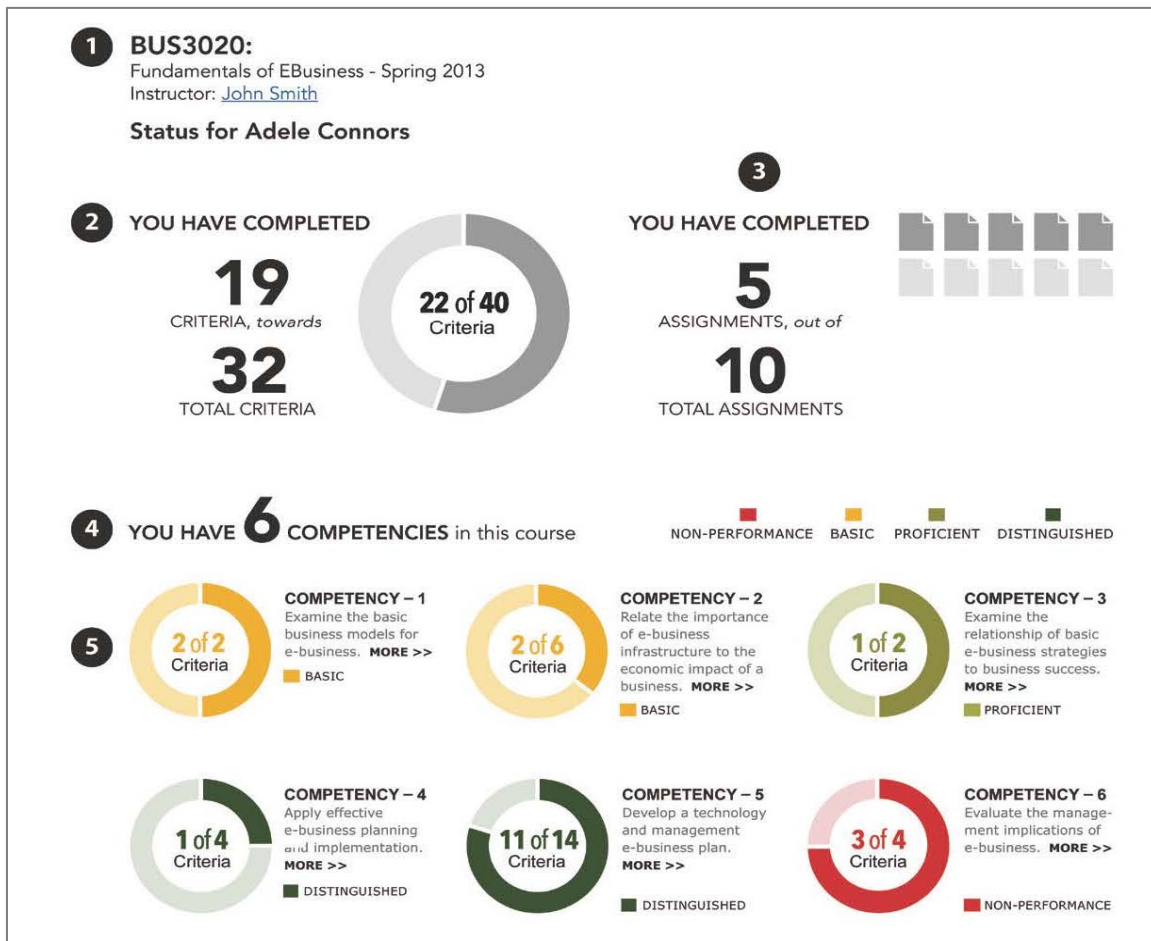
Source: Capella University[75]

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[75] "Capella Launches Innovative Competency Map Dashboard to Align Student Learning with Employer Needs." Capella University, October 23, 2013. https://www.capella.edu/about/why-choose-capella-university/competency-based-education/

SECTION III: BEST PRACTICES

This section presents a selection of best practices and recommendations drawn from published literature, government agencies, and institutional lessons learned. These recommendations are not exhaustive but address several different aspects of learning analytics.

ANALYTICS STRATEGY DEVELOPMENT

- **Engage senior institutional leaders to provide a strategic direction for and organizational commitment to learning analytics.** This may be best achieved by integrating a learning analytics strategy with broader institutional planning.[76]

- **Seek input diverse stakeholders when developing the analytics strategy, not just those with technology expertise.** Ensuring that all key stakeholders are involved helps to create a robust strategy that will serve all major interests from the beginning. In particular, stakeholders from IT should "join with assessment, curriculum, and instruction staff, as well as top decision makers, and work together to iteratively develop and improve data collection, processing, analysis, and dissemination."[77]

- **Design a customized strategy; the most appropriate strategy for one higher education institution will differ from the best strategy for another.** An institution's strategy should be sensitive to the university's particular conditions. Analytics will be most useful when they address specific, important academic and/or business challenges facing the institution.[78]

- **Assess the institution's current data and reporting landscape to determine realistic possibilities and necessary adjustments**.[79] An analytics strategy must determine what resources are currently available, as well as whether any changes are needed to how existing data are collected or who is responsible for oversight and maintenance of current data.

- **Proactively identify risks and obstacles early when developing an analytics strategic.** The strategic plan should incorporate measures to address these issues initially and in the future as learning analytics are adopted over time. Typical inhibitors include:[80]
  - Cost
  - Difficulty of keeping pace with developments in analytics tools and techniques
  - Concerns about misuse of data
  - Challenges working with vendors (e.g., system transparency and vendor lock-in)

- **Start small and leverage the work of others.** Purchasing and implementing large-scale systems, as well as the data integration necessary for large analytics solutions, can incur significant costs and difficulty. It may be useful to begin with descriptive analytics

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[76] Colvin et al., Op. cit., p. 18.
[77] Bienkowski, Feng, and Means, Op. cit., p. 46.
[78] Arroway et al., Op. cit., p. 32.
[79] Ibid., p. 33.
[80] Ibid.

before attempting to implement predictive systems.[81] Starting with small pilot applications can test an initiative and help to build an organizational culture receptive to analytics. Low-cost or open solutions and data sets may assist with implementing these small initial projects.[82] There is no single analytics "silver bullet" that will immediately solve problems if a large-scale solution is enacted. Incremental adoption can allow an institution to "set the foundation for good data analysis and then start answering many little questions, each of which will contribute to student success."[83]

DATA STANDARDS AND GOVERNANCE

- **Establish governance positions and procedures.** While universities may have existing structures, agreements, and processes for collecting and working with student data, these already-established structures may not appropriately cover new learning analytics implementations. Oversight and policies should address:[84]
    - Data types to be used for learning analytics and collection processes
    - Anonymization of the data where appropriate
    - Analytics processes to be performed and their purposes/expected outcomes
    - Retention and stewardship of data used for and generated by learning analytics
- **Create and maintain data privacy standards and procedures.** Access to student data should be restricted to individuals with a legitimate need. However, additional access may be granted if data is anonymized. Privacy procedures should take care to monitor anonymization processes to avoid identification via metadata or aggregation of data.[85]
- **Implement and maintain data consent procedures.** "Students will normally be asked for their consent for personal interventions to be taken based on the learning analytics. This may take place during the enrolment process or subsequently. There may be legal, safeguarding, or other circumstances where students are not permitted to opt out of such interventions. If so, these must be clearly stated and justified."[86] Institutions should clearly describe to students and parents what data is collected and how/why it is used to avoid mistrust issues.
- **Include data interpretation conventions when developing standards.** To be most effective, LA strategies typically involve data that can be shared across personnel and departments. A group of LA experts from Australia and other countries emphasized that "conventions for the interpretation of data events and standards for identifying data instances are essential preconditions for the flow of data that is necessary for crucial comparisons (e.g., better/worse)."[87]

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[81] Ibid.
[82] Bienkowski, Feng, and Means, Op. cit., p. 47.
[83] Sharkey, M. "The Ins and Outs of Analytics." Educause Review, October 7, 2013.
    http://er.educause.edu/articles/2013/10/the-ins-and-outs-of-analytics
[84] Sclater, N. and P. Bailey. "Code of Practice for Learning Analytics." Jisc, June 4, 2015.
    https://www.jisc.ac.uk/guides/code-of-practice-for-learning-analytics
[85] Sclater and Bailey, Op. cit.
[86] Ibid.
[87] Colvin et al., Op. cit., p. 18.

DATA COMPLETENESS AND ACCURACY

- **Establish data governance procedures to ensure that data is as clean, accurate, consistent, and complete as possible.** In addition to the basic risks associated with taking action based on faulty data, inaccurate or incomplete data can damage or erode trust. Students, staff, and members of the public may resent and oppose learning analytics programs that do not demonstrate trustworthy data practices. International HEIs report using data governance initiatives and assigned data stewards to improve data quality and improve perceptions of analytics efforts.[88]

- **Consider relevant but unavailable data when analyzing data or planning future action.** For example, analytics on time-to-degree or retention only demonstrate an internal perspective derived from an institution's collected data, with potential inclusion of data from other compatible systems. However, a variety of important mitigating aspects, such as "personal and noncognitive factors such as family responsibilities, work schedules, and behavioral patterns," are likely to be omitted from institutional data capture.[89]

DATA USABILITY AND INTEGRATION

- **Standardize data formats where possible to allow for integration between different systems.** Focus group discussion with higher education personnel indicate that the disparate systems relevant to analytics frequently use different data formats that may not be interoperable.[90] Consistent data formats and processes can that data from one system is compatible with data from another, making analysis easier. Many software packages and platforms are built to integrate data.

- **Provide tools so various stakeholders can interact with appropriate data**. End users should be able to access, manipulate, and confirm data as much as possible. Furthermore, this level of manipulation and visibility may help reinforce the understanding that analytical projections and outputs (e.g., student risk levels) are conjectures. This reinforces "active, critical engagement with analytics representations, rather than passive consumption."[91]

METRICS

- **Select metrics carefully to ensure that they target and support desired outcomes.** Data analysis derives conclusions and predictions from the set of available metrics. Therefore, if the metrics are not appropriately selected, there is a risk that, at best, the desired outcomes are not possible, or, at worst, they can lead to negative practices and habits. One source emphasizes: "If the final assessment rewards undesired

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[88] Arroway et al., Op. cit., p. 15.
[89] Ibid., p. 11.
[90] Ibid., p. 15.
[91] Colvin et al., Op. cit., p. 18.

behavior, improving the control system to more effectively optimize the results will make the learning worse."[92]

■ **If requesting data from students directly, avoid "survey exhaustion."** The University of Michigan's E²Coach system initially required students to complete the survey each time they wanted to access their next message to update the profile. As a result, many students stopped using the system. Later, the University found that the system could operate based only on the initial survey.[93] In some cases, repeat measures may be unavoidable, but these should be made as simple as possible to obtain.

TOOLS

■ **Make data manipulation and visualization tools as user-friendly as possible.** Clear and easy to use systems allow staff or students to not only understand the data, but to translate the information into action. Students and staff are more likely to make regular and full use of a tool that is simple and pleasant to use. For students, appropriately usable tools can support student empowerment by encouraging and enabling students to "take increasing responsibility for their own learning, rather than control student behavior or mechanically direct students to resources."[94]

■ **Dashboards should be integrated with the learning management system (LMS) already at use within the university.[95]** This limits the number of separate locations students or other users need to access to view pertinent information, and may also reduce the number of credentials users are required to retain if single sign-on (SSO) systems are not in place.

■ **Consider LMS improvements when implementing learning analytics**. Much analytics data derives from the institutional LMS, and adding features and expanding use of the LMS will increase the data usable for analysis and potentially increase student engagement with the system. EDUCAUSE surveys of LMS systems across a significant number of global higher education institutions report that nearly half (46 percent) of students believe that better LMS features are needed, most commonly in the following areas:[96]

  o Communication mechanisms (e.g., IM, video chat, online tutoring, social group discussions and forums, and access to other students' contact information)
  o Alerts and calendaring (e.g., posting grades, assignment due dates, exam reminders)
  o Grading tools (e.g., calculating and projecting)
  o Multimedia access (e.g., recorded lectures and podcasts)
  o Mobile interface (e.g., access from smartphones and tablets)

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[92] Clow, "The Learning Analytics Cycle," Op. cit., p. 137.
[93] Huberth, Michelotti, and McKay, Op. cit.
[94] Colvin et al., Op. cit., p. 19.
[95] Reimers and Neovesky, Op. cit., p. 400.
[96] Dahlstrom, E., D.C. Brooks, and J. Bichsel. "The Current Ecosystem of Learning Management Systems in Higher Education: Student, Faculty, and IT Perspectives." Educause Center for Analysis and Research, September 2014. p. 19. https://net.educause.edu/ir/library/pdf/ers1414.pdf

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