macmillan learning

Empowering Analytics for Instructors

An approach to analytics for instructors informed by Learning Sciences research

Goal, Overview, and Application

Goal

At Macmillan, our goal is to drive better learner outcomes. A fundamental part of our approach is to apply findings from the Learning Sciences to product design, improvement, implementation, and support.

Overview

Here we provide overarching principles for the design of effective analytics for instructors derived from a synthesis of the learning science literature. In addition, we provide examples of insights and dashboard reporting elements for instructors that leverage these principles.

Application

These overarching principles underpin the design of Macmillan's analytics features and capabilities. However, these principles may also be applied by institutions, instructors, and instructional technologists to their own learning experiences.

Research Foundation and Process

Foundation

These principles are based upon a thorough literature review of educational and cognitive psychology research by learning researchers.

Process

These principles were developed through a rigorous and comprehensive ten-step research and refinement process that included:

- Primary and secondary literature review and synthesis by Macmillan Learning Research team
- Design of principles by Macmillan Learning Research team
- Internal review by 4 Macmillan Learning scientists
- External review by 7 students
- External review by 5 experts comprising Macmillan Learning's Learning Research Advisory Board

All of these researchers, contributors and reviewers are listed to the right.

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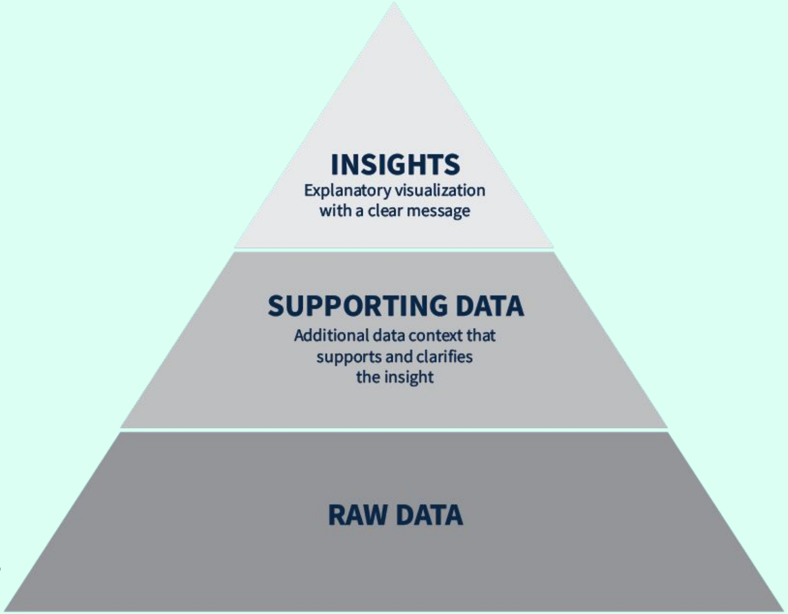
What educational analytics are actionable and for whom?

The term analytics is often used in different ways. For our purposes, we define analytics as the meaningful combining, computing, and visualizing of data into actionable insights.

Analytics that support effective teaching and learning are always actionable. They answer key stakeholder questions. They provide holistic, valid, and reliable insights into learner progress and performance — taking into consideration data from all aspects of the learning experience including cognitive, noncognitive, and behavioral inputs — and facilitate effective and efficient action. They provide insights that answer specific questions, while also facilitating the ability to seek additional information via supporting and raw data.

They provide learners with feedback, support metacognition and self-regulation, bolster motivation, and foster interaction and collaboration. As such, principles for analytics span many different areas of the learning sciences literature.



Overarching Principles for Actionable Analytics

Report Against Learning Objectives

Learning objectives enable analytics that provide all stakeholders within the learning experience to monitor and improve mastery of concepts, application of skills, and development of attributes.

Provide Strategic Feedback

Strategic (timely, specific, targeted) feedback enables learners to better understand their current performance, how they should be performing, and how they can close the gap between the two.

Support Metacognition and Self-Regulation

Analytics can help learners more accurately and efficiently gauge their progress and adjust their practices accordingly, supporting improved metacognitive abilities and better self-regulated learning strategies.

Foster Motivation

Bolstering learner motivation and self-efficacy improves learner persistence, affect, and performance.

Enhance Interaction and Collaboration

Fostering productive instructor-to-learner and learner-to-learner interaction and collaboration increases learner engagement and performance.

Enable Effective Interventions

Providing valid insights (visualized in ways that reduce extraneous cognitive load) and supporting effective and efficient interventions enhances the experience of all stakeholders involved in the learning process.

Two broad categories of analytics

By combining analytics from each of these categories, stronger insights can be derived and more effective interventions can be enabled

Checkpoint Analytics

Indicate whether students interacted with materials or progressed as planned

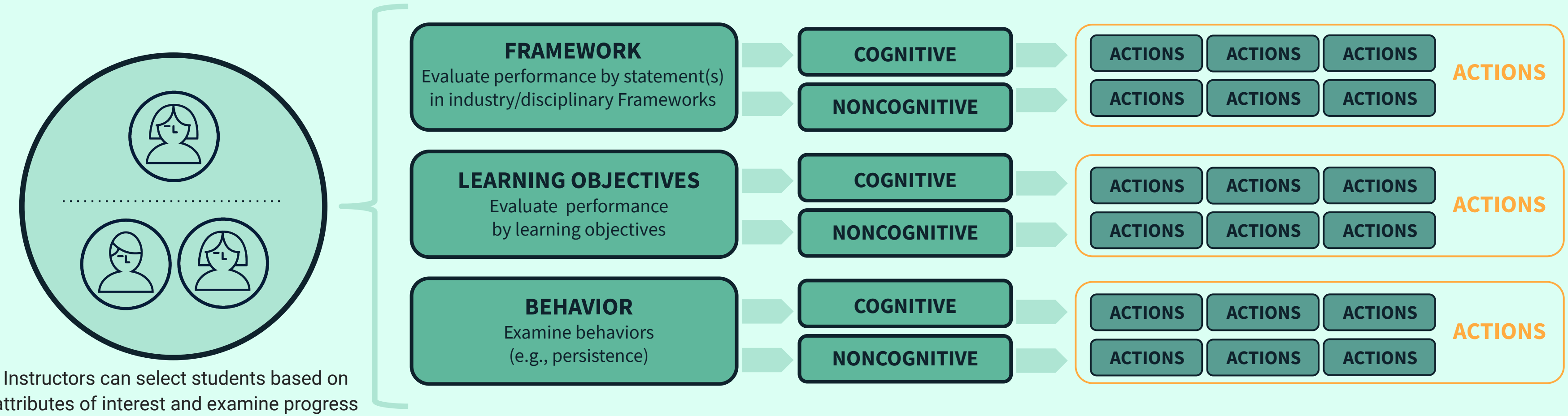
Process Analytics

Indicate student information processing and knowledge application

CATEGORIES	CHECKPOINT ANALYTICS	PROCESS ANALYTICS
Gauge Progress on Learning Objectives	*E.g., Learner access of resources aligned to a given learning objective*	*E.g., Learner performance reporting aligned to any given learning objective*
Provide Strategic Feedback	*E.g., Learner access of instructor- or peer-provided feedback*	*E.g., Learner performance improvement(s) according to rubric application across versions submitted*
Support Metacognition & Self-regulation	*E.g., Learner time-on-task associated with reflection activities*	*E.g., Learner reflection responses — quality (depth, breadth)*
Foster Motivation	*E.g., Learner access of supplementary learning resources*	*E.g., Learner self-report levels of intrinsic versus extrinsic motivation*
Enhance Interaction and Collaboration	*E.g., Learner access of interactive learning resources*	*E.g., Learner interactions on collaborative features (e.g., discussion board) — quantity of responses, quality (depth, breadth)*

Essential Elements of Instructor Dashboard

Ability to view student performance at individual and cohort levels by framework, learning objectives, and behaviors. This data can be further analyzed by cognitive and noncognitive dimensions with the ability to then take one or more actions.



Instructors can select students based on attributes of interest and examine progress and performance accordingly

Instructor Feedback

“Process, as it is illustrated here is about application of learning as opposed to simply undertaking a task.” - Dr. Thomas

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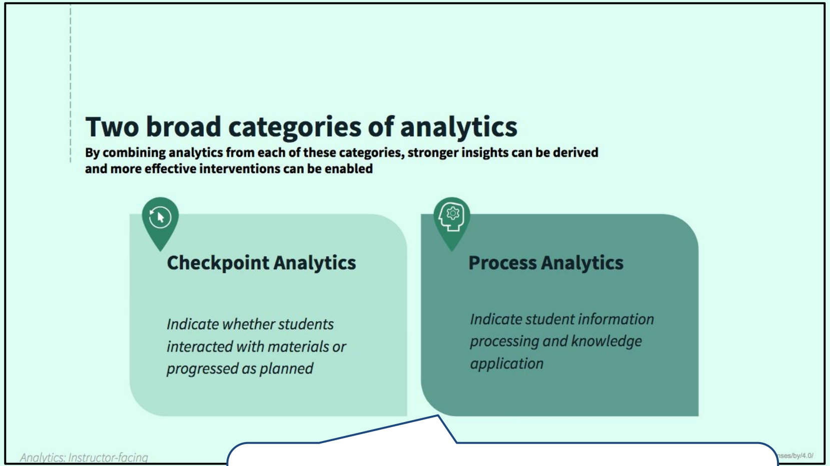
		E.g., Learner interactions on collaborative features ... quantity of responses,

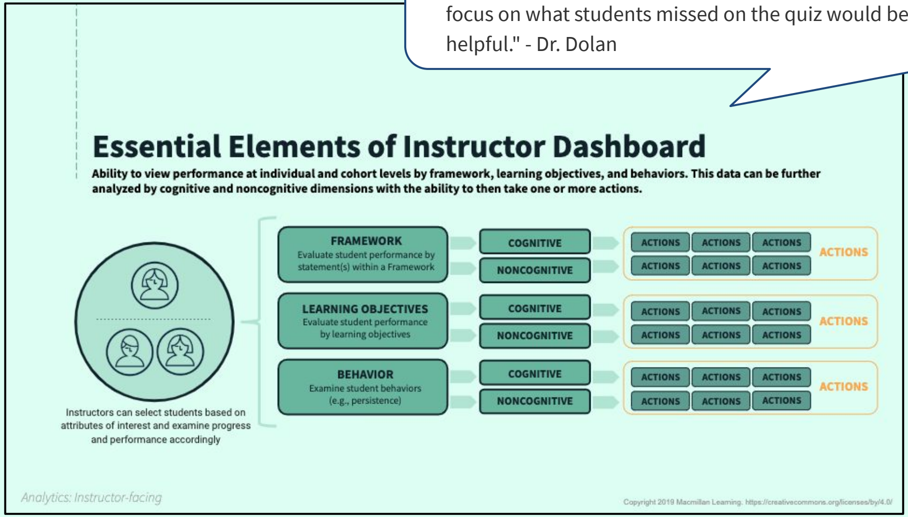
“Analytics that span these factors and gauge both use of material and success using the material allow for fine-grained insight into affect student learning, progress, and success.” - Dr. Dolan



“This analytic structure provides more holistic insights that should allow both instructors and students to take more strategic action.” - Dr. Dolan

Instructor Feedback

"A dashboard that will allow me to quickly prioritize current materials (e.g., quiz taken within the past couple of days) and focus on what students missed on the quiz would be super helpful." - Dr. Dolan



References

Almeda, V., Baker, R., & Corbett, A. (2017). Help avoidance: When students should seek help, and the consequences of failing to do so. Teachers College Record, (119)3, 1-24.

Arnold, K. E. (2010). Signals: Applying academic analytics. Educause Quarterly, 33(1), n1.

Berland, M., Baker, R. S., & Blikstein, P. (2014). Educational data mining and learning analytics: Applications to constructionist research. Technology, Knowledge and Learning, 19(1-2), 205-220.

Bodily, R. & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. IEEE Transactions on Learning Technologies, PP(99), 2-15.

Bowers, A.J. (2010). Analyzing the Longitudinal K-12 Grading Histories of Entire Cohorts of Students: Grades, Data Driven Decision Making, Dropping Out and Hierarchical Cluster Analysis. Practical Assessment, Research & Evaluation (PARE), 15(7), 1-18.

Brown, P., Roediger, H., & McDaniel, M. (2014). Make it stick: The science of successful learning. Cambridge MA: Harvard University Press.

Bussey, K. & Bandura, A. (1999). Social cognitive theory of gender development and differentiation. Psychology Review 106(4), 676-713.

Cerezo, R., Sanchez-Santillan, M., Paule-Ruiz, M., & Nunez, J. (2016). Students' LMS interaction patterns and their relationship with achievement: A case study in higher education. Computers & Education, 96, 42-54.

Charleer, S., Klerkx, J., Duval, E., De Laet, T., & Verbert, K. (2016). Creating effective learning analytics dashboards: Lessons learnt. In European Conference on Technology Enhanced Learning (pp. 42-56). Springer International Publishing.

Cheng, G. (2017). The impact of online automated feedback on students' reflective journal writing in an EFL course. The Internet and Higher Education, 34, 18-27.

Cho, M., Kim, Y., & Choi, D. (2017). The effect of self-regulated learning on college students' perceptions of community of inquiry and affective outcomes in online learning. The Internet and Higher Education, 34, 10-17.

Collins, K., Onwuegbuzie, A., & Jiao, Q. (2008). Reading ability and computer-related attitudes among African American Graduate Students. Cyberpsychology & Behavior, 11(3), 347-350.

Cooper, J. (2006). The digital divide: The special case of gender. Journal of Computer Assisted Learning, 22, 320-334.

Corrin, L., & de Barba, P. (2014). Exploring students' interpretation of feedback delivered through learning analytics dashboards. In B. Hegarty, J. McDonald, & S.K. Loke (Eds.), Rhetoric and reality: Critical perspectives on educational technology. Proceedings ascilite Dunedin 2014 (pp. 629-633).

Davis, E. A. (2003). Prompting middle school science students for productive reflection: Generic and directed prompts. The Journal of the Learning Sciences, 12(1), 91-142.

Dawson, S. (2010). “Seeing” the learning community: An exploration of the development of a resource for monitoring online student networking. British Journal of Educational Technology, 41(5), 736-752.

Dawson, S. P., McWilliam, E., & Tan, J. (2008). Teaching smarter: How mining ICT data can inform and improve learning and teaching practice. Annual Conference of the Australasian Society for Computers in Learning in Tertiary Education, 221-230. Melbourne, Australia: Deakin University.

Durall, E., & Gros, B. (2014). Learning analytics as a metacognitive tool. 6th International Conference on Computer Supported Education, 380-384.

References

Frisby, B., Berger, E., Burchett, M., Herovic, E., & Strawser, M. (2014). Participation apprehensive students: The influence of face support and instructor-student rapport on classroom participation. Communication Education, 63(2), 105-123.

Garrison, D. R. & Arbaugh, J. B. (2007). Researching the community of inquiry framework: Review, issues, and future directions. The Internet and Higher Education, 10, 157-172.

Gomez-Aguilar, D. A., Hernandez-Garcia, A., Garcia-Penalvo, F. J., & Theron, R. (2014). Tap into visual analysis of customization of grouping of activities in eLearning. Computers in Human Behavior, 47, 60-67.

Hattie, J. & Timperley, H. (2007). The power of feedback. Review of Educational Research, 77(1), 81-112.

Hershkovitz, A., Nachmias, R. (2008) Developing a log-based motivation measuring tool. Proceedings of the 1st International Conference on Educational Data Mining, 226-233.

Hu, Y., Lo, C., & Shih, S. (2014). Developing early warning systems to predict students' online learning performance. Computers in Human Behavior, 36, 469-478.

Ifenthaler, D. (2012). Determining the effectiveness of prompts for self-regulated learning in problem-solving scenarios. Educational Technology & Society, 15(1), 38-52.

Kim, I. (2014). Development of reasoning skills through participation in collaborative synchronous online discussions. Interactive Learning Environments, 22(4), 467-484.

Kotsiantis, S., Tselios, N., Filippidi, A., & Komis, V. (2013). Using learning analytics to identify successful learners in a blended learning course. International Journal of Technology Enhanced Learning, 5(2), 133-150.

Lazowski, R.A., & Hulleman, C.S. (2016). Motivation interventions in education: A meta-analytic review. Review of Educational Research, 86(2), 602-640.

Lockyear, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. American Behavioral Scientist, 57(10), 1439-1459.

Lonn, S., Aguilar, S. J., & Teasley, S. D. (2015). Investigating student motivation in the context of a learning analytics intervention during a summer bridge program. Computers in Human Behavior, 47, 90-97.

Macfadyen, L. P. & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. Computers & Education, 54(2), 588-599.

Murray, M., Perez, J., Geist, D., & Hedrick, A. (2012). Student interaction with online course content: Build it and they might come. Journal of Information Technology Education: Research, 11, 125-140.

Park, Y. & Jo, I. (2015). Development of the learning analytics dashboard to support students' learning performance. Journal of Universal Computer Science, 21(1), 110-133.

Rienties, B., Boroowa, A., Cross, S., Kubiak, C., Mayles, K., & Murphy, S. (2016). Analytics4Action evaluation framework: A review of evidence based learning analytics interventions at the Open University UK. Journal of Interactive Media in Education, 1(2), 1-11.

Rowe, F. A., & Rafferty, J. A. (2013). Instructional design interventions for supporting self-regulated learning: Enhancing academic outcomes in postsecondary e-learning environments. Journal of Online Learning and Teaching, 9(4), 590-601.

Santos, O. Boticario, J. Perez-Marin, D. (2014). Extending web-based educational systems with personalised support through user centred designed recommendations along the e-learning life cycle. Science of Computer Programming, 88, 92-109.

References

Scheffel, M., Drachsler, H., Stoyanov, S., & Specht, M. (2014). Quality indicators for learning analytics. Educational Technology & Society, 17(4), 117-132.

Schumacher, C. & Ifenthaler, C. (2017). Features students really expect from learning analytics. Computers in Human Behavior, 1-11. [In press]

Segedy, J. R., Kinnebrew, J. S., & Biswas, G. (2015). Using coherence analysis to characterize self-regulated learning behaviours in open-ended learning environments. Journal of Learning Analytics, 2(1), 13-48.

Sung, E. & Mayer, R. (2012). Five facets of social presence in online distance education. Computers in Human Behavior, 28, 1738-1747.

Tempelaar, D.T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. Computers in Human Behavior, 47, 157-167.

Thomson, A., Perry, J., Miller, T. (2009). Conceptualizing and measuring collaboration. Journal of Public Administration Research and Theory, 19, 23-56.

van Blankenstein, F., Dolmans, D., van der Vleuten, C., & Schmidt, H. (2011). Which cognitive processes support learning during small-group discussion? The role of providing explanations and listening to others. Instructional Science, 39, 189-204.

van Leeuwen, A., Janssen, J., Erkens, G., & Brekelmans, M. (2014). Supporting teachers in guiding collaborating students: Effects of learning analytics in CSCL. Computers & Education, 79, 28-39.

van Leeuwen, A., Janssen, J., Erkens, G., & Brekelmans, M. (2015). Teacher regulation of cognitive activities during student collaboration: Effects of learning analytics. Computers & Education, 90, 80-94.

Veenman, M. V. J. (2017). Assessing metacognitive deficiencies and effectively instructing metacognitive skills. Teachers College Record, 119(13).

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. American Behavioral Scientist, 57(10), 1500-1509.

Verbert. K., Govaerts, S., Duval, E., Santos, J., van Assche, F., Parra, G., & Klerkx, J. (2014). Learning dashboards: An overview and future research opportunities. Personal and Ubiquitous Computing, 18(6), 1499-1514.

Wise, A. F. (2014, March). Designing pedagogical interventions to support student use of learning analytics. In Proceedings of the Fourth International Conference on Learning Analytics And Knowledge (pp. 203-211). ACM.

Yoo, Y., Lee, H., Jo, I., & Park, Y. (2015). Educational dashboards for smart learning: Review of case studies. In Chen, G., Kumar, V., Huang, R., & Kong, S. (eds). Emerging Issues in Smart Learning. Lecture Notes in Educational Technology. Berlin, Germany: Springer-Verlag Berlin Heidelberg.

Zimmerman, B. J. (2008). Goal setting: A key proactive source of academic self-regulation. In D. H. Schunk & B. J. Zimmerman (Eds.), Motivation and Self-Regulated Learning: Theory, Research, and Applications (pp.267-295). New York: Lawrence Erlbaum Associates.