Empowering Analytics for Students

An approach to analytics for students informed by Learning Sciences research

Goal, Overview, and Application

Goal

At Macmillan, our goal is to drive 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 students derived from a synthesis of the learning science literature. In addition, we provide examples of insights and dashboard reporting elements for students that leverage these principles.

Application

These overarching principles underpin how we're developing next generation learning products. However, they 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 research and cognitive psychology 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 Macmillan Learning's Learning Research Advisory Board

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

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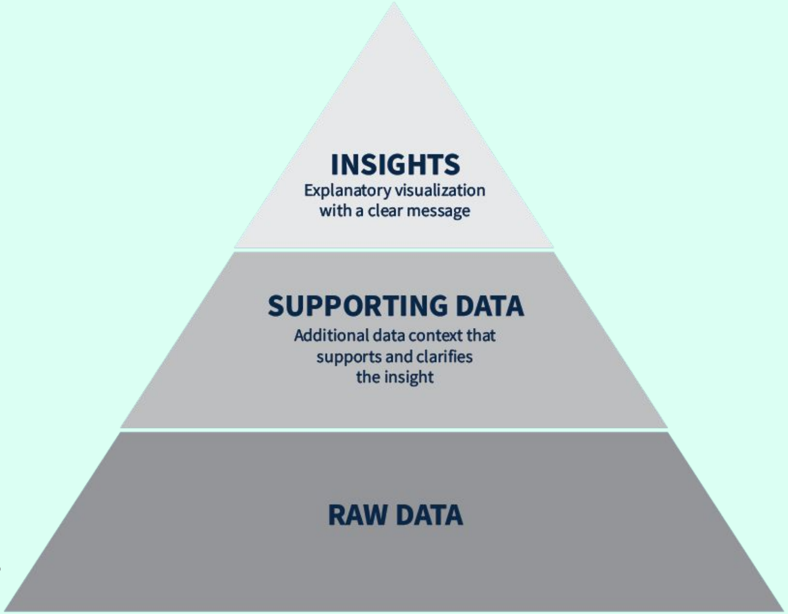
What educational analytics are actionable and for whom?

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
Report Against 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 a scoring rubric prior to beginning the assignment*	*E.g., Identification of like rubric element(s) a learner consistently struggles with across assignments*
Support Metacognition & Self-regulation	*E.g., Learner access of assignment-specific learning strategy resources*	*E.g., Learner levels of self-reported understanding vs. actual performance*
Foster Motivation	*E.g., Learner access of goal-setting capabilities*	*E.g., Learner levels of self-efficacy*
Enhance Interaction and Collaboration	*E.g., Learner access of instructor office hour scheduling capabilities*	*E.g., Learner contributions on collaborative activities according to peer review*

Analytics: Student-facing

Essential Elements of Learner Dashboard

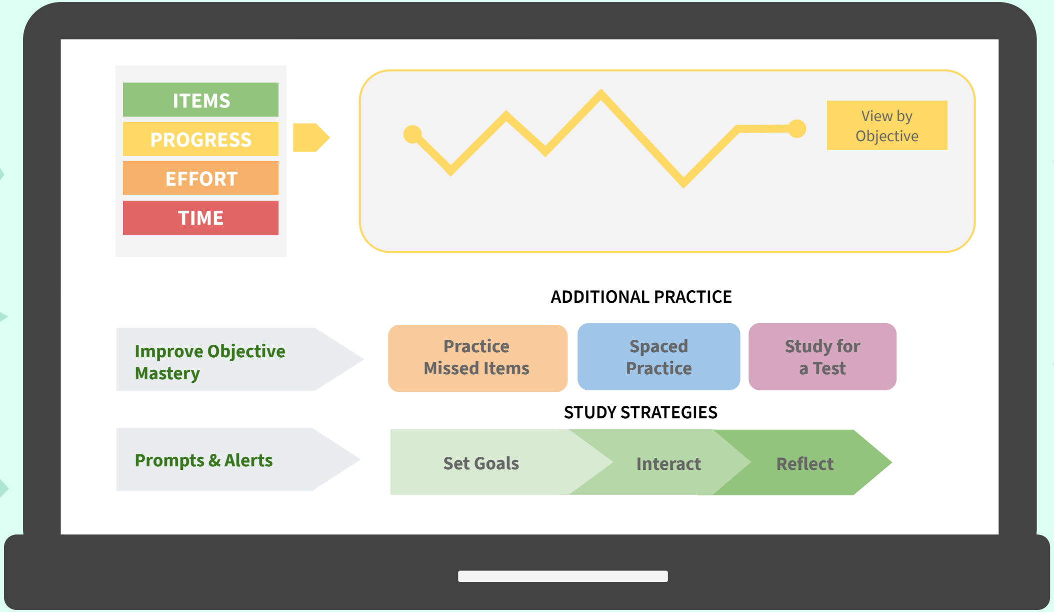
To Support Monitoring of Progress and Action

Visual representation of progress and performance

Clear communication of performance across multiple dimensions

Ability to improve mastery of objectives

Ability to receive and respond to prompts: reminders, alerts, recommendations (mobile)



Performance by objective (and topic for market readiness)

Ability to practice for a variety of purposes (close gaps, improve transfer, or test prep)

Ability to improve study strategies and learning regulation

Instructor and Student Feedback

“Analytics are helpful for directing what subjects I need to focus on. I like knowing how I am doing in the course and it prevents me from guessing what I need to work on. I want to try and avoid missing topics or not dedicating too little or too much time to a topic.” - Student Codesign Group Member

Essential Elements of Learner Dashboard

“Analytics are helpful if they are tied to specific learning objectives. Any type of assessment should be founded on the desired learning objective, so it makes sense for analytics to provide measures and data towards that goal as well.” - Student Codesign Group Member

“This slide provides a helpful overview of the types of information a learner dashboard could present and how it would be beneficial.” - Dr. Thomas

“I like this, nice visual layout!” - Dr. Dolan

“An outstanding concrete feature. The pertinent information is displayed and it’s all easily digested.” - Dr. McDaniel

“I’ve enjoyed using dashboards to check my progress and performance on homework assignments and exams. Moreover, I appreciate being able to view my performance against the aggregate performance of the entire class. For instance, for each exam, the dashboard created a bar graph laying out the spread of classroom scores.” - Student Codesign Group Member

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