Institutional Analytics for Transformation

Análisis institucional para la transformación

Análise institucional para a transformação

Ryan S. Baker[1]

Received: October 20th, 2025
Accepted: December 3rd, 2025
Available: January 13th, 2026

How to cite this article:
Baker, R. (2026). Institutional Analytics for Transformation. *Rastros Rostros, 28*(1), 1-29.
doi: https://doi.org/10.16925/2382-4921.2026.01.01

Research article. https://doi.org/10.16925/2382-4921.2026.01.01

[1] Adelaide University.
E-mail: ryanshaunbaker@gmail.com
ORCID: https://orcid.org/0000-0002-3051-3232

Abstract

Learning analytics—the systematic use of educational data to understand and optimize learning—has emerged as a powerful approach for addressing persistent challenges in higher education, including student dropout, incomplete learning, and inequitable outcomes. This article examines how learning analytics can benefit institutions, particularly multi-campus universities in contexts where such approaches have not been widely applied, by drawing on successful examples from higher education and K-12 settings worldwide. Taking a socio-technical perspective, the article emphasizes that realizing the potential of analytics requires careful attention to both technological capabilities and human practices, policies, and ethical principles.

The article explores diverse applications across key stakeholder groups: instructors benefit from dashboards that surface at-risk students and inform pedagogical decisions; students receive personalized nudges and course recommendations that promote success; digital learning platforms leverage analytics to adapt content and detect disengagement; advisors use integrated systems to prioritize outreach; and program directors identify curricular improvements and less-effective teaching. Throughout, the article grounds recommendations in core ethical principles—transparency, privacy, consent, fairness, de-biasing, and accountability—that must underpin responsible analytics practice.

However, the promise of learning analytics is tempered by significant implementational challenges. Technical limitations, design failures, and institutional resistance can undermine even well-intentioned initiatives. The article identifies critical obstacles including insufficient data infrastructure, alert fatigue when predictions are not embedded in actionable workflows, lack of stakeholder buy-in from instructors and IT departments, and difficulties scaling pilots across diverse campuses and programs. Addressing these challenges requires moving beyond purely technical solutions to treating analytics as part of broader organizational change.

To support successful implementation, the article advocates for iterative design processes informed by best practices from the learning sciences, human-computer interaction, and universal design. It emphasizes establishing feedback loops where institutions systematically collect data, analyze effectiveness, engage stakeholders in co-design, and refine both models and workflows. Professional development for data literacy, clear governance structures with cross-campus representation, designated roles for learning designers and implementation coordinators, and robust data stewardship all emerge as essential conditions for sustained success.

For multi-campus universities—particularly in settings where regional differences in connectivity, student demographics, and institutional capacity are significant—the article stresses the importance of balancing standardization with local adaptation, ensuring equitable benefit across contexts, and building capacity through mixed teams combining technical expertise with deep pedagogical understanding. Practical recommendations include conducting comprehensive data audits, negotiating vendor contracts to secure fine-grained event data, establishing privacy-preserving data linkage systems, and investing deliberately in professional development that embeds data literacy into everyday academic practice.

The article concludes by addressing emerging frontiers, including the transformative potential and ethical challenges posed by generative AI, and by offering concrete next steps for institutional leaders: get data systems ready, establish iterative design and governance processes, secure appropriate expertise, invest in capacity building, and above all, center equity, ethics, and student agency. By foregrounding these principles and treating learning analytics as a sustained commitment rather than a one-time project, institutions can harness data to widen educational opportunity, support evidence-informed improvement, and uphold public trust in the responsible use of technology in higher education.

Keywords: learning analytics, student success, implementation, multi-campus university, socio-technical systems

Resumen

La analítica del aprendizaje —el uso sistemático de datos educativos para comprender y optimizar el aprendizaje— se ha convertido en un enfoque eficaz para abordar los desafíos persistentes en la educación superior, como la deserción estudiantil, el aprendizaje incompleto y la desigualdad en los resultados. Este artículo examina cómo la analítica del aprendizaje puede beneficiar a las instituciones, en particular a las universidades multicampus en contextos donde estos enfoques no se han aplicado ampliamente, basándose en ejemplos exitosos de la educación superior y la educación primaria y secundaria en todo el mundo. Desde una perspectiva sociotécnica, el artículo enfatiza que aprovechar el potencial de la analítica requiere una cuidadosa atención tanto a las capacidades tecnológicas como a las prácticas humanas, las políticas y los principios éticos.

El artículo explora diversas aplicaciones en grupos clave de partes interesadas: los instructores se benefician de paneles que identifican a los estudiantes en riesgo e informan las decisiones pedagógicas; los estudiantes reciben recordatorios personalizados y recomendaciones de cursos que promueven el éxito; las plataformas de aprendizaje digital aprovechan la analítica para adaptar el contenido y detectar la desconexión; los asesores utilizan sistemas integrados para priorizar la divulgación; y los directores de programa identifican mejoras curriculares y la enseñanza menos efectiva. A lo largo de todo el artículo, las recomendaciones se basan en principios éticos fundamentales (transparencia, privacidad, consentimiento, equidad, eliminación de sesgos y rendición de cuentas) que deben sustentar una práctica analítica responsable.

Sin embargo, la promesa de la analítica del aprendizaje se ve limitada por importantes desafíos de implementación. Las limitaciones técnicas, los fallos de diseño y la resistencia institucional pueden socavar incluso las iniciativas bienintencionadas. El artículo identifica obstáculos críticos, como la infraestructura de datos insuficiente, la fatiga de alertas cuando las predicciones no se integran en flujos de trabajo viables, la falta de aceptación de las partes interesadas (instructores y departamentos de TI), y las dificultades para escalar los pilotos en diversos campus y programas. Abordar estos desafíos requiere ir más allá de las soluciones puramente técnicas y considerar la analítica como parte de un cambio organizacional más amplio.

Para respaldar una implementación exitosa, el artículo aboga por procesos de diseño iterativos basados en las mejores prácticas de las ciencias del aprendizaje, la interacción persona-computadora y el diseño universal. Hace hincapié en el establecimiento de ciclos de retroalimentación donde las instituciones recopilan datos sistemáticamente, analizan la eficacia, involucran a las partes interesadas en el codiseño y perfeccionan tanto los modelos como los flujos de trabajo. El desarrollo profesional para la alfabetización de datos, las estructuras de gobernanza claras con representación intercampus, los roles designados para los diseñadores de aprendizaje y los coordinadores de implementación, y una sólida gestión de datos se convierten en condiciones esenciales para un éxito sostenido.

Para las universidades con múltiples campus, en particular en entornos con diferencias regionales significativas en conectividad, demografía estudiantil y capacidad institucional, el artículo destaca la importancia de equilibrar la estandarización con la adaptación local, garantizar beneficios equitativos en todos los contextos y desarrollar capacidades mediante equipos mixtos que combinen la experiencia técnica con un profundo conocimiento pedagógico. Entre las recomendaciones prácticas se incluyen la realización de auditorías de datos exhaustivas, la negociación de contratos con proveedores para asegurar datos de eventos de granularidad precisa, el establecimiento de sistemas de vinculación de datos que preserven la privacidad y la inversión deliberada en desarrollo profesional que integre la alfabetización de datos en la práctica académica diaria.

El artículo concluye abordando las nuevas fronteras, incluyendo el potencial transformador y los desafíos éticos que plantea la IA generativa, y ofreciendo próximos pasos concretos para los líderes institucionales: preparar los sistemas de datos, establecer procesos iterativos de diseño y gobernanza, asegurar la experiencia adecuada, invertir en el desarrollo de capacidades y, sobre todo, priorizar la equidad, la ética y la autonomía estudiantil. Al priorizar estos principios y considerar la analítica del aprendizaje como un compromiso sostenido en lugar de un proyecto puntual, las instituciones pueden aprovechar los datos para ampliar las oportunidades educativas, impulsar mejoras basadas en la evidencia y mantener la confianza pública en el uso responsable de la tecnología en la educación superior.

Palabras clave: analítica del aprendizaje, éxito estudiantil, implementación, universidad multicampus, sistemas sociotécnicos

Resumo

A análise da aprendizagem —o uso sistemático de dados educativos para compreender e otimizar a aprendizagem— se transformou em uma abordagem eficaz para abordar os desafios persistentes na educação superior, como a deserção estudantil, a aprendizagem incompleta e a desigualdade nos resultados. Este artigo examina como a análise da aprendizagem pode beneficiar as instituições, em particular as universidades multicampus em contextos onde essas abordagens não foram aplicadas amplamente, com base em exemplos exitosos da educação superior e da educação primária e secundária em todo o mundo. A partir de uma perspectiva sociotécnica, o artigo enfatiza que aproveitar o potencial da análise requer um cuidado e atenção tanto às capacidades tecnológicas como às práticas humanas, às políticas e aos princípios éticos.

O artigo explora diversas aplicações em grupos clave de partes interessadas: os instrutores se beneficiam de painéis que identificam os estudantes em risco e informam as decisões pedagógicas; os estudantes recebem registros personalizados e recomendações de cursos que promovem até o sucesso; as plataformas de aprendizagem digital aproveitam a análise para adaptar o conteúdo e detectar a desconexão; os assessores utilizam sistemas integrados para priorizar a divulgação; e os diretores do programa identificam melhores currículos e o ensino é menos eficaz. Ao longo de todo o artigo, as recomendações são baseadas em princípios éticos fundamentais (transparência, privacidade, consentimento, equidade, eliminação de sessões e entrega de contas) que devem sustentar uma prática analítica responsável.

No entanto, a promessa de análise de aprendizagem é limitada por importantes desafios de implementação. As limitações técnicas, as falhas de design e a resistência institucional podem sovar até as iniciativas bienintencionadas. O artigo identifica obstáculos críticos, como a infraestrutura de dados insuficiente, a fadiga de alertas quando as previsões não se integram aos fluxos de trabalho viáveis, a falta de aceitação das partes interessadas (instrutores e departamentos de TI) e as dificuldades para escalar os pilotos em diversos campi e programas. Abordar esses desafios requer mais soluções puramente técnicas e considerar a análise como parte de uma mudança organizacional mais ampla.

Para respaldar uma implementação exitosa, o artigo acima é um processo de design iterativo baseado nas melhores práticas das ciências do aprendizado, na interação pessoa-computador e no design universal. Isso foi feito no estabelecimento de ciclos de retroalimentação onde as instituições coletaram dados sistematicamente, analisaram a eficácia, envolveram as partes interessadas no código e aperfeiçoaram tanto os modelos quanto os fluxos de trabalho. O desenvolvimento profissional para a alfabetização de dados, as estruturas de governança claras com representação intercampus, as funções designadas para os designers de aprendizagem e os coordenadores de implementação, e uma gestão sólida de dados são convertidas em condições essenciais para um sucesso sustentado.

Para universidades com múltiplos campus, em particular em ambientes com diferenças regionais decorrentes de conectividade, demografia estudantil e capacidade institucional, o artigo destaca a importância de equilibrar a normatização com a adaptação local, garantir benefícios equitativos em todos os contextos e desenvolver capacidades por meio de equipamentos mistos que combinam a experiência técnica com um conhecimento pedagógico profundo. Entre as recomendações práticas estão a realização de auditorias de dados exaustivas, a negociação de contratos com provedores para garantir dados de eventos de granularidade precisa, o estabelecimento de sistemas de vinculação de dados que preservam a privacidade e a inversão deliberada no desenvolvimento profissional que integra a alfabetização de dados na prática acadêmica diária.

O artigo conclui abordando as novas fronteiras, incluindo o potencial transformador e os desafios éticos que plantam IA generativa, e oferecendo próximos passos concretos para os líderes institucionais: preparar os sistemas de dados, estabelecer processos iterativos de design e governança, garantir a experiência adequada, inverter o desenvolvimento de capacidades e, sobre tudo, priorizar a equidade, a ética e a autonomia estudantil. Ao priorizar esses princípios e considerar a análise da aprendizagem como um compromisso sustentado em vez de um projeto pontual, as instituições podem aprovar os dados para ampliar as oportunidades educativas, impulsionar melhorias baseadas na evidência e manter a confiança pública no uso responsável da tecnologia na educação superior.

Palavras-chave: análise de aprendizagem, estudo de sucesso

Introduction

In the last 15-20 years, there has been considerable enthusiasm for the potential that data can bring for improving academic practices, processes, and outcomes, in higher education, K-12, and beyond. These efforts have gone by multiple names -- such as institutional analytics, academic analytics, learning analytics, educational data mining, educational data science -- reflecting different emphases. Institutional analytics refers to the systematic use of integrated institutional data—spanning enrolment, finance, human resources, student support, and learning systems—to inform strategic planning, resource allocation, risk management, and quality assurance at the whole-of-institution level, extending the traditions of institutional research through modern data infrastructure and governance (Weil et al., 2023). Academic analytics, by contrast, more narrowly denotes the application of predictive modelling and other data mining techniques to academic data (such as recruitment, progression, and programme performance indicators) to support evidence-informed decision-making by institutional leaders, with a primary focus on accountability and organisational effectiveness rather than direct intervention in individual learning processes (Campbell et al., 2007). Learning analytics is more tightly focused on applications related to learner support and pedagogy, and has been defined as “the measurement, collection, analysis and reporting of data about learners and their contexts for the purpose of understanding and optimising learning and the environments in which it occurs” (Baker & Siemens, 2013). While all three approaches draw on overlapping datasets and methods, institutional and academic analytics operate at higher levels to steer institutional strategy and performance, whereas learning analytics emphasises lower levels, directly informing teaching, learning design, and personalised support for learners (Long & Siemens, 2011). In general, these areas are all differentiated from the older area of institutional research which has traditionally prioritised descriptive reporting, compliance, and periodic studies in support of accreditation and planning, and is less focused—at least historically—on real-time, integrated, and predictive uses of data to drive continuous, multi-level decision-making (Volkwein, 1999).

Analytics can enhance the functioning of higher education institutions by enabling more timely, targeted, and evidence-based responses to persistent challenges such as high drop-out and incomplete/poor student learning. By integrating data from learning management systems, student information systems, advising records, and engagement tools, institutions can identify at-risk students earlier, understand where and why learning breakdowns occur, and tailor interventions such as proactive advising, curriculum redesign, supplemental instruction, and adaptive feedback to specific learner needs (Arnold & Pistilli, 2012; Sclater et al., 2016). At the same time, analytics can surface structural patterns—such as bottleneck courses, inequitable progression pathways, or ineffective pedagogical practices—supporting systemic changes that improve both student success and institutional effectiveness (Long & Siemens, 2011; Gašević et al., 2015). These analytics-driven efforts are even more necessary given the disruptions to higher education caused by generative AI, which simultaneously challenges traditional assessment integrity, obscures evidence of individual learning, and accelerates shifts in student expectations and labour-market demands (Lee et al., 2024; Smolansky et al., 2023).

In this article, I will discuss how learning analytics can benefit higher education, taking a socio-technical lens in considering the practices and policies that can facilitate and take advantage of the potential of technology and data while considering the human impacts of those technologies (Buckingham Shum & Shibiani, 2019). I will consider successful examples at both a coarser-grained level (e.g. dropout prevention, curriculum analytics) and a finer-grained level (e.g. content refinement, knowledge tracing, short-term engagement detection). I will discuss examples both from higher education and K-12 education, focusing on how these examples are or can be made relevant to higher education in a multi-campus university in Colombia.

Throughout the article, I will attempt to ground discussion and recommendations in core ethical principles that underpin the appropriate and beneficent use of analytics in education (cf. Slade & Prinsloo, 2013; Pardo & Siemens, 2014). Transparency requires that institutions clearly communicate what data are collected, how they are used, and what implications they may have for students and staff. Privacy requires that analytics practices rigorously minimise, secure, and appropriately separate personal data, ensuring that individuals' identities and intimate details are protected from unwarranted access, use, or surveillance. Consent demands that learners are provided with genuine choice and intelligible information about participation in analytics-related activities, rather than relying solely on opaque, blanket agreements, while not necessarily requiring the same level of constant detailed verification of consent that is sometimes used for human subjects research not intended to benefit subjects. Fairness entails designing and applying analytics in ways that avoid systematic disadvantage for particular groups and that support equitable access to opportunities and support. De-biasing calls for ongoing identification and mitigation of historical, technical, and interpretive biases embedded in data, models, and institutional practices. Accountability requires that clear lines of responsibility, oversight, and redress are established so that harms are recognised, owned, and meaningfully addressed. All of this takes place in the context of legal frameworks, regulations, and policies that govern acceptable use of data and requirements around what is and is not allowable in education.

Learning Analytics for Academic Decision-Making and Learning Support

There are a great number of ways that learning analytics can be used to support academic decision making. First of all, there is an extremely wide variety of learning analytics methods (Saqr & Lopez-Pernas, 2024; Baker, 2025). One common framework divides methods by the type of analysis, into prediction models, structure discovery, and relationship mining (Baker & Yacef, 2009; Baker, 2025). Another perspective divides methods by the type of use of the analytics, dividing analytics into descriptive, predictive, and prescriptive models (Susnjak, 2024). Within this framework, descriptive analytics summarise existing data to provide insight into patterns of learner engagement, performance, and progression. Predictive analytics use historical and real-time data to estimate the likelihood of future outcomes, positive or negative. Prescriptive analytics go a step further by recommending concrete actions or interventions that are likely to improve outcomes.

Instructors. One of the core audiences for analytics is instructors. One of the most common types of support given to instructors is dashboards, which transform complex, multi-source data into concise visual and (sometimes) interactive summaries of student engagement, performance, and progression, with the intention of supporting timely sense-making and pedagogical decision-making (Verbert et al., 2020). When they are well aligned with course context and instructor needs, such dashboards can help identify at-risk students earlier, highlight bottleneck concepts or activities, and prompt more targeted feedback, communication, and redesign of learning tasks (Kaliisa et al., 2024). They can also help to surface important information from course activities that otherwise would be inscrutable to instructors, such as group work or student-AI interactions (Alfredo et al., 2024; Baker et al., in press). If designed to integrate into learning platforms or learning management systems used across a university system, dashboards can provide scaled benefit for multi-campus university systems. Beyond dashboards, learning analytics can support instructors by informing the design and timing of feedback, highlighting when and how to intervene with individuals or groups, and enabling continuous refinement of course structures and assessments (Lockyer, Heathcote, & Dawson, 2013). By supporting instructors in knowing which students to intervene with, and scaffolding them in doing so, systems based around learning analytics can substantially enhance instructor-student relationships and support experiences, even for very large courses (Iraj et al., 2021).

Students. Learning analytics can also directly support students through personalised, data-informed guidance that helps them avoid dropout and course failure and make choices that lead to better outcomes. Automated nudges—delivered via email, SMS, or in-platform notifications and triggered by indicators such as inactivity, missing submissions, or declining performance—can provide timely, specific prompts to re-engage with key activities, access support services, or adjust study strategies (Arnold & Pistilli, 2012; Brown et al., 2023). In doing so, it is important to design these systems to support motivation and belongingness, and to design to promote positive outcomes as well as designing to avoiding negative outcomes. At a coarser grain size, course-recommendation systems can support students' decision making by using historical performance, prerequisite structures, workload patterns, and declared goals to suggest suitable courses and sequences—highlighting combinations associated with successful progression for similar learners and warning against choices linked to overload or failure risk (Yu et al., 2021). In applying such systems, it is important to avoid unintended consequences coming from making recommendations to individual students in isolation, such as recommending that every student in the university take the same elective.

Use in Digital Learning Platforms. Another major way that learning analytics can support learners is through its use in digital learning platforms. Digital learning platforms offer interactive experiences to learners, offering greater adaptivity than traditional learning activities. Initially restricted to tightly scaffolded activities (e.g. Anderson et al., 1995), and highly expensive to author (Murray, Blessing, & Ainsworth, 2013), generative AI has recently made it much less expensive to develop intelligent support for a wider range of content and types of learning activities (Calo & Maclellan, 2024; Baker et al., in press). Even prior to generative AI, learning analytics made it possible to infer student knowledge on both straightforward and complex knowledge (Pelanek, 2017), to infer student disengagement (Baker & Ocumpaugh, 2014), and to determine where in a curriculum a student should start (Cosyn et al., 2021). Such systems have been repeatedly demonstrated to produce significant benefits to learners (see meta-analysis in Kulik & Fletcher, 2016). With new support for scaling across content domains from generative AI, AI-supported digital learning platforms are becoming an increasing part of higher education and K-12 worldwide.

Advisors. Academic advisors are another critical audience for learning analytics, particularly when analytics are tightly integrated into advisee tracking systems (often implemented within CRMs -- Custom Relationship Management tools) and caseload management tools to support proactive, comprehensive student support. Modern advising systems increasingly combine progression data (e.g., credit accumulation, program milestones, course success patterns), engagement indicators (e.g., LMS activity, attendance, assessment submission), and, in some cases, signals related to disengagement such as repeated withdrawals, to generate risk flags and prioritised caseload views that help advisors decide which students to contact, when, and about what (Jayaprakash et al., 2014; Rust & Motz, 2025). When designed and implemented well, these tools enable earlier targeted outreach and support, embedding analytics into advisors' everyday workflows rather than adding parallel systems, and supporting advisors' professional judgment instead of substituting for it (Kyte et al., 2023).

Program Directors. Increasingly, analytics also supports program directors (or, where more relevant, department heads) in decision-making, a valuable type of support when managing large or multi-site degree programs. Tools can support identifying less effective instructors (Koedel & Rockoff, 2015), including instructors with high failure rates, lower rates of student retention within program, or poorer performance on high-stakes examinations, enabling interventions or where absolutely necessary, replacement. Learning analytics can also recommend more effective curricular progressions, identifying when a course needs another course first as a prerequisite (Stavrinides & Zuev, 2023). Analytics can also be useful at a finer-grained level to recommend course improvements, through identifying content that does not help students learn as well (Baker et al., 2018) or less-useful assessment items (Adetutu & Lawal, 2022) thereby supporting iterative adjustments to content, pacing, and assessment policies.

Core Implementational Challenges for Universities at Early Stage of Implementation. Although the promise of learning analytics is high, the success of learning analytics interventions in universities has varied -- from highly successful initiatives (Malcolm, Milliron, & Kil, 2014) to less publicized interventions that failed for a variety of reasons. There are three particularly salient categories of challenge: 1) Technical challenges, where the effectiveness of learning analytics solutions is insufficient, perhaps due to limitations in the data available or skill gaps in the team conducting algorithmic work; 2) Design challenges, where the technology is sufficiently good, but the design for how it is used fails for various reasons, including insufficient understanding of student or teacher needs or of pedagogy in general; 3) Institutional challenges, where various stakeholders on campus are resistant or simply insufficiently committed to the initiative to cooperate, participate, and provide resources as needed for its success. In this section, I discuss some of the primary challenges of each of these types in greater detail.

One of the core areas of challenge that can involve challenges at the design and institutional levels is ensuring that AI-generated alerts become meaningful actions. For example, simply generating a list of “at-risk” students, no matter how accurate, does not guarantee that anyone will have the time, mandate, or confidence to respond. A well-designed system must therefore specify clear workflows and ownership (for example, whether responsibility lies with central advisors, course coordinators, or student support units), provide staff with actionable guidance rather than opaque risk scores, and align the timing of alerts with points in the semester when intervention is still feasible. At the institutional level, leaders must commit resources to staffing, training, and coordination so that alerts do not simply add to workload or become background noise amid competing priorities. Without such commitments, even technically strong systems can produce alert fatigue, inconsistent follow-through, and inequitable patterns of support, where some students receive timely help and others do not. In short, the challenge is not only to predict which students are at risk, but to embed those predictions in organisational processes, professional practice, and support structures that reliably translate data into effective and sustainable action. This highlights the importance of treating analytics as a part of broader support strategies rather than treating it as purely a technical problem (Atif et al., 2020; Imundo et al., 2025).

Relatedly, it is important to gain the buy-in of important stakeholders such as instructors and academic advisors. If these actors perceive learning analytics as a surveillance tool, a threat to their professional autonomy, or simply as an additional administrative burden, they may disengage, ignore dashboards and alerts, or actively resist implementation. Building buy-in requires not only clear communication about the goals and boundaries of the system (for example, what data are and are not used, and how predictions will and will not be employed), but also genuine opportunities for stakeholders to shape indicators, intervention protocols, and governance arrangements. Professional development must focus on helping staff interpret analytics in light of their disciplinary expertise and local knowledge of students, rather than positioning the system as a replacement for human judgment. When instructors and advisors see that analytics can support rather than supplant their work, and when they are confident that the system is trustworthy, fair, and responsive to feedback, they are more likely to incorporate it into their daily practice and to advocate for its continued refinement and institutionalization.

Similarly, resistance or lack of buy-in from information technology departments can be a risk for a learning analytics initiative. IT units are often asked to provision data pipelines, create and maintain integrations with the institution's learning management system and student information systems, ensure security and privacy, and support uptime and scalability, all on top of already stretched workloads and competing institutional priorities. If learning analytics is perceived as "someone else's project," or if it is championed solely from an academic or student success unit without early and ongoing IT involvement, critical technical dependencies may be under-resourced, delayed, or implemented in fragile ways that undermine long-term sustainability. Securing IT buy-in typically requires explicit recognition of their strategic role, clear articulation of how learning analytics aligns with broader institutional digital and data strategies, and realistic planning around infrastructure, staffing, and support. Establishing cross-functional governance structures, involving IT leaders in key decision-making, and setting shared expectations about timelines, service levels, and data governance can help ensure that learning analytics is built on robust, secure, and maintainable systems rather than ad hoc workarounds that are vulnerable to failure or abandonment as soon as a high-level champion departs.

Finally, attention needs to be paid when scaling pilots beyond initial programs, units, and campuses -- both guaranteeing learning analytics models remain valid, and that implementation remains consistent and high quality. Models that work well in one department, campus, or student population may degrade in performance when underlying curricula, assessment practices, student demographics, or teaching modalities differ, leading to substantial drops in accuracy. At the same time, local adaptation is often needed so that analytics align with program-level goals and cultures, which can pull against the desire for a single, standardised institutional solution. Addressing this tension requires systematic processes for model validation and recalibration across contexts; clear documentation of model assumptions and intended uses; and governance mechanisms that determine when local tailoring is appropriate and when consistency is essential (for example, in risk thresholds linked to institutional interventions). It also demands ongoing monitoring for model drift over time as programmes evolve, along with structured feedback from frontline users about how well the analytics fit their practice. Without these processes, institutions risk a situation where some programs benefit from carefully tuned analytics and others use outdated, poorly calibrated models or abandon the system entirely.

Part II – Development, Evaluation & Continuous Improvement

In light of all the challenges listed above, it may seem daunting to think about developing learning analytics solutions, particularly in a context where they have not been applied before, such as a multi-campus university in Colombia without a tradition of the application of learning analytics. In such a setting, challenges include not only the novelty of the methods themselves, but also the need to coordinate practices across geographically distributed campuses that serve students with markedly different socio-economic backgrounds, prior educational experiences, and levels of digital access.

Fortunately, as the examples above show, there are a number of past examples, across a wide diversity of institutions serving students from kindergarten to graduate students, that demonstrate that learning analytics initiatives can succeed. In this section, we discuss some of the approaches that can increase the likelihood of success.

Use of Good Design Principles and Design Approaches

One of the primary paths to a successful solution is to build off past successful approaches. As the sections above indicate, there are a great number of past successes to learn from. As such, one core approach is to identify which past initiatives are most similar to a specific initiative of interest, and then study the approaches that led those initiatives to succeed or fail. For instance, a project attempting to implement a student success initiative using predictive modeling to reduce dropout might look to projects such as Purdue Course Signals (Arnold & Pistilli, 2012), Georgia State's learning analytics initiative (Krumm et al., 2018), Projeto Ceibal (Queiroga et al., 2022), or the BrightBytes Early Warning System (Esbenshade et al., 2023). Or, to give another example, a project attempting to empower instructors with data on student learning could consider the lessons learned from projects such as ASSISTments (Feng & Heffernan, 2006) or Queensland Course Insights (Khosravi et al., 2021). A project need not have been a complete success or sustained to be informative -- for example, BrightBytes was closed down after a corporate acquisition, but its lessons remain relevant. While many of these projects may come from different contexts than the current project's context, specifics of their approaches are likely to be informative. For a multi-campus university in Colombia, part of the design task is likely to be to translate these lessons into a regulatory and cultural context where national policy priorities (for example, around equity of access and regional development) and accreditation expectations may differ from the settings in which these initiatives were originally developed. This includes considering how practices proven in highly resourced environments with heavy use of online learning can be adapted for campuses where connectivity, device access, and local support structures vary substantially. It may also mean deliberately prioritising constructs linked to known challenges for local students—such as transitions from secondary to tertiary education or balancing study with work—so that analytics respond to the realities of the student body in each campus and program.

Beyond this, several areas of scholarship and practice have important lessons for developing a learning analytics approach. Work in the learning sciences and cognitive science highlights the importance of aligning analytics with well-established principles of how people learn, such as spacing and interleaving of practice, timely formative feedback, and support for metacognition and self-regulated learning; dashboards and alerts that are grounded in these principles (e.g. Molenaar et al., 2019; Outerbridge & Taub, 2025) are more likely to drive changes in teaching and study behaviour. Insights from this literature can also help teams prioritise which constructs to model.

Human–Computer Interaction and usability engineering provide complementary guidance on how to make analytics tools actually usable and useful in everyday practice. Approaches such as participatory design, iterative prototyping, and systematic usability testing can help ensure that interfaces are usable by instructors and advisors, and that they fit into their work patterns. Good HCI practice also encourages attention to explainability and transparency (core themes in the learning analytics literature as well -- see Khosravi et al., 2022), so that users can understand where indicators come from and how to act on them, instead of being presented with opaque scores that are hard to understand and may not be trusted.

Universal design offers further guidance, emphasising that systems should be designed to be usable by the widest possible range of users from the outset, rather than retrofitting accommodations for learners with disabilities later (Rose, 2000). Applying universal design principles to learning analytics means ensuring that dashboards and communications are accessible (for example, in terms of visual design, language, and device compatibility), and that interventions do not inadvertently privilege students with particular forms of cultural, linguistic, or digital capital. It also encourages teams to consider how analytics-supported interventions can provide multiple pathways for students to engage with support and to demonstrate learning, so that "success" is not defined in a narrow way that systematically disadvantages particular groups. For a Colombian university with campuses in different regions, universal design also entails attending to linguistic and cultural variation—for example, ensuring that messages and dashboards are understandable and resonant for students whose schooling histories, language repertoires, and local labour-market expectations differ. It may also require designing for low-bandwidth or mobile-first use for students who are less likely to have reliable broadband or personal laptops.

Feedback Loops for Improvement

One of the core lessons learned from the human-computer interaction literature is the need for feedback loops for improvement. One process is to have cycles of collecting data on the current situation, studying what is working and not working, engaging in reflection and design with key stakeholders (as many as feasible), and then designing or re-designing.

For example, one might start by noting that dropout rates are high, and then systematically collecting historical data and analysing the factors associated with dropout, such as patterns of course access, assessment submissions, and use of digital resources. The next step is then identifying which of these factors most strongly differentiate students who complete from those who withdraw or fail. These findings can then be brought to advisors, instructors, and relevant support staff to discuss their plausibility, interpret the patterns in light of local practices, and collaboratively sketch what kinds of information and prompts would be most helpful in supporting at-risk students. Based on that joint analysis and reflection, the team can then design and pilot a system that uses what was learned to provide instructors with actionable recommendations. For example, such a system could recommend that an academic advisor call a student when the model determines in week 2 of the semester that a student is likely to fail their course because they have not opened the e-textbook yet. (This is in fact a practice adopted by Southern New Hampshire University based on a process of this nature -- Baker et al., 2015).

At this point, a second iterative loop begins. The institution can monitor how often instructors and advisors act on the recommendations, gather qualitative feedback on whether the suggestions are feasible and useful, and analyse whether courses using the system show improvements in student engagement, retention, or grades compared to similar courses without the system. It may become clear that some alerts are too frequent or too late to be helpful, that the recommended actions need to be tailored to different disciplines, or that the model behaves differently for particular student groups. These insights can then guide refinements to both the predictive model (for example, adjusting thresholds or adding new features) and the surrounding workflows and interfaces (for example, simplifying alert messages or integrating them into existing advising tools). In this way, learning analytics implementation becomes a continuous, participatory cycle of design, evaluation, and redesign, rather than a one-time deployment of a fixed system.

Eventually, the evidence generated from this type of endeavor can be incorporated into broader quality-assurance reviews and preparation for accreditation by demonstrating that the institution systematically monitors student outcomes, evaluates the impact of interventions, and refines its practices over time. Documentation of the analytics models, the decision rules they support, and the results of successive cycles of piloting and revision can serve as concrete artefacts showing that continuous improvement is embedded in institutional processes rather than occurring on an ad hoc basis. In addition, analyses disaggregated by campus, programme, and student subgroup can provide accrediting bodies with evidence that the institution is attentive to equity, consistency, and effectiveness across its diverse contexts, and is willing to adjust its systems when unintended disparities are detected. In this way, learning analytics is not only a tool for day-to-day student support, but also a source of robust, longitudinal evidence that underpins institutional claims about the quality and effectiveness of its teaching and support systems, helping to ensure accountability.

A key consideration when evaluating the success of an initiative during iterative design is choosing the right set of indicators to consider. A set of indicators should be as comprehensive as possible, considering the impacts on students, instructors, and the broader university community in as many ways as possible. For example, for students it is important not only to track traditional outcomes such as retention, grades, and time to degree, but also measures of engagement and sense of belonging. For instructors and advisors, indicators might include changes in workload, patterns of tool use, perceived decision support, and effects on professional autonomy or satisfaction. At the institutional level, relevant indicators could include the scalability and reliability of the technical infrastructure, budgetary implications, alignment with strategic goals, and evidence of reduced inequities across campuses, programmes, or demographic groups (including students in different regions). It is also valuable to include indicators of potential unintended consequences, such as over-reliance on quantitative indicators, stigmatisation of students labelled “at risk,” or widening gaps in support between programmes that adopt the tools enthusiastically and those that do not. By examining a broad and balanced set of indicators, teams are better positioned to judge whether an initiative is genuinely advancing educational quality and equity, rather than simply improving a narrow set of metrics.

Two key types of stakeholders during this development process (beyond the aforementioned groups) are learning design teams and implementation coordinators. Two key types of stakeholders during this development process (beyond the aforementioned groups) are learning design teams and implementation coordinators. Learning designers can help ensure that analytics are tightly aligned (where appropriate) with course outcomes, assessment structures, and pedagogical intentions, for example by identifying where actionable feedback fits naturally into the student experience. They are also well positioned to anticipate how changes in curriculum or assessment will affect the meaning of indicators over time, and to surface design tensions when analytics suggest trade-offs (for instance, between flexibility and structure in course design). Implementation coordinators, play a distinct and pivotal role in managing communication, timelines, and dependencies across departments and campuses, helping to ensure that pilots are launched on schedule, that training and support are available when needed, and that lessons learned in one context are captured and shared with others, and that differences between contexts and campuses are taken into account. They can also help monitor fidelity of implementation—whether the tools and workflows are being used as intended—and coordinate feedback from diverse stakeholders back to the technical and design teams. Many K-12 initiatives in particular have noted the essential role that implementation coordinators play in both development and in scaling of learning analytics initiatives (e.g. Baker et al., 2004; Khachatryan, 2020). Together, these roles help bridge the gap between technical development, pedagogical intent, and day-to-day practice, increasing the likelihood that learning analytics initiatives are coherent, sustainable, and scalable.

Institutional Culture and Capacity Building

Institutional culture and capacity are central to whether learning analytics becomes a sustained, responsible practice or remains a short-lived project. Effective governance bodies typically include representatives from academic units, student services, IT, institutional research, and, where possible, students themselves, so that decisions about indicators, interventions, and data use reflect diverse perspectives. In a Colombian multi-campus system, it is especially important that these bodies include representation from different campuses and regions, so that decisions do not inadvertently reflect only the priorities and practices of one campus. These groups can set policies for how analytics is used, provide oversight on data access and use policies, and review evidence for effectiveness and risks to equity. Over time, transparent and participatory governance processes help build trust that analytics are being used in ways that respect academic values and student rights, as well as ensuring that the interests of university staff charged with implementing interventions are taken into account.

As part of this, accountability structures are needed to ensure that learning analytics supports, rather than undermines, evidence-based decision-making. Accountability in this context does not simply mean holding individuals responsible for hitting numeric targets; instead, it means establishing clear expectations about how data will be used to improve teaching and support, and then regularly reviewing whether those expectations are being met. For example, governance bodies can require that major analytics initiatives specify their theory of change, identify equity-focused and unintended-consequence indicators alongside traditional outcomes, and report regularly on both achievements and problems. Departments and programmes may be asked to show how analytics findings have informed their curriculum reviews, advising models, or resource allocations. When accountability is framed in terms of reflective use of evidence—and supported by robust data, appropriate indicators, and a culture that values learning and improvement—it reinforces a virtuous cycle in which analytics are used thoughtfully to enhance student success and institutional quality, rather than as blunt instruments for monitoring or control.

These goals of governance and accountability intersect with professional development (also discussed above). At most institutions, some degree of capacity building is needed to effectively use and manage learning analytics. Data literacy initiatives and other forms of professional development form a key pillar of capacity building, extending beyond technical training to support a broader culture of evidence-informed decision-making. Educators and advisors need support not only in reading dashboards, but also in interpreting uncertainty, recognising the limits of predictive models, and combining quantitative indicators with their professional judgment and local knowledge of students. University leaders and department heads similarly benefit from professional development on how to pose good questions to analytics teams, how to avoid simplistic uses of metrics for performance management, and how to effectively use evidence to evaluate programmes and policies. These efforts can be integrated into existing professional learning structures—such as teaching academies, induction programmes, and leadership development courses—so that “thinking with data” becomes a normal part of how the institution operates rather than a specialised skill confined to a few experts.

Data Systems

A final key area of development involves university data systems. In a very real sense, learning analytics runs on data. If data systems are insufficient, learning analytics is unlikely to reach anywhere near its full potential, regardless of what other elements are in place. Any university or university system wanting to implement learning analytics should immediately review its data -- not taking for granted that just because data exists on campus that the data is high-quality and in a usable form. For a multi-campus university system, this review must account for the possibility that different campuses rely on distinct legacy systems, have uneven levels of digitisation of records, or have adopted different local tools over time, making integration and standardisation a non-trivial task.

The first step is to make sure that all the necessary data is actually being collected. Some learning management system vendors do not actually provide data to a university unless explicitly required to by a contract. Other vendors provide low-quality data, leading to very high cost to universities in pre-processing data or possibly not having access to key data fields needed for analysis. Universities should demand that their vendors provide fine-grained data at the level of individual actions, where specific identifiers such as learning resources and courses can be mapped back to specific resources and courses; this cannot be taken for granted, even from very large vendors.

The next step is to assemble and link all of the types of data that are needed. This may include learning management systems, student information systems, customer relationship management systems (often used for tracking advisor-student contact), library use, satisfaction and course evaluation surveys, and even data sources like video watching analytics. At the same time, steps should be taken to avoid use of data that causes privacy concerns, such as dorm room card swipes (e.g. Bradberry et al., 2017). Institutions may also wish to explore how internal data can be responsibly linked to external sources such as national examinations. In linking data, it is important to find an identifier that can link across all these disparate forms of data while not retaining personally identifying information in data sets that would be problematic if leaked. The typical solution is to have a strictly-guarded key, where data is linked using personally identifying information but then that information is swapped for a coded number, with the mapping between that coded number and personally identifying information stored carefully and accessible to only a small number of individuals (Khalil & Ebner, 2016).

Relatedly, it is important to establish clear roles and responsibilities for maintaining data quality and ethical use, often through designated data stewards (the individuals who may have access to a strictly-guarded key, for instance). Data stewards or data custodians can be responsible for specific systems or domains (for example, LMS data, student information system data, or advising data), with explicit accountability for documenting data definitions, monitoring data quality, overseeing access controls, and ensuring that updates or system changes do not inadvertently compromise the integrity of analytics. Their work should be embedded within a broader governance framework (as discussed above) that specifies who is authorised to request and use which data, for what purposes, and through what approval processes, including review for ethical and privacy implications. Clear role descriptions, decision rights, and escalation pathways help prevent situations where analytics projects proceed without adequate oversight, or where sensitive data is accessed informally because no one is quite sure who owns it. By pairing technical infrastructure with well-defined stewardship and governance roles, institutions can support the reliable, ethical, and sustainable use of data for learning analytics. In a multi-campus university, it can be helpful to designate both central data stewards and campus-level liaisons, so that local practices and concerns are visible in institutional decision-making about data, and campus staff know whom to approach when questions about data quality, interpretation, or ethics arise.

Part III --- Conclusion & Future Directions

As this review indicates, learning analytics has become an important contributor to the quality of education in both universities and in K-12, providing benefits in areas spanning from at-risk intervention, to curricular refinement, to adaptive learning. These benefits have been driven by a combination of classical machine learning and data mining, with design and data-driven decision making practices. The combination of artificial intelligence and human intelligence into thoughtfully-designed systems has benefited countless learners, and the field continues to work to develop better tools, dashboards, and methods to improve outcomes further.

Several areas remain focuses of considerable efforts in learning analytics research, with possible implications for practice in the medium-term. One emerging challenge is determining which recommendation is the best recommendation for a specific situation: when (is as usual) a given situation has several possible responses, researchers are exploring how to match interventions to particular students, courses, and moments in time, and how to learn from prior intervention-outcome pairs to improve those matches (Ju et al., 2020). A second active area concerns determining the long-term effects of interventions, moving beyond short-term changes in behaviour or grades to understand whether particular uses of analytics improve persistence, learning, and post-graduation outcomes (Poquet et al., 2021). At the same time, as analytics-supported interventions become more pervasive, there is growing attention to maintaining student agency, by designing systems that support informed choice rather than nudging students in invisible ways (Hooshyar et al., 2023). Relatedly, there is increased interest in transparency, where students can see, contest, and meaningfully respond to data about themselves (Bodily et al., 2018). Finally, researchers and practitioners are increasingly concerned with shifting student attitudes towards learning analytics, building trust that data are being used to support rather than for surveillance, that systems are fair, and that students have a voice in how analytics shape their educational experience.

Another area of considerable recent interest is the potential role of generative artificial intelligence. The recent advent of generative AI such as large language models has already produced methodological upgrades for several areas of learning analytics, most notably adaptive learning systems, as discussed briefly above. Generative AI produces new opportunities, for rapidly creating new course content and lesson plans (Lin et al., 2025), providing rapid feedback to learners (Pankiewicz & Baker, 2023), scaling deep feedback (Stahl et al., 2024), and creating educational chatbots that are available 24/7 (Google, 2025).

However, these advances also produces new challenges that the field has yet to fully address. For instance, students may use generative AI in their assignments in ways that are not permitted by their instructors, viewed by many as a form of cheating. At the moment, tools for detecting cheating by using LLMs are insufficiently accurate, and it is unclear if this will change. Some institutions are moving to in-person assessments as a method of reducing cheating, but this is difficult to scale and even this may eventually be possible to cheat with augmented reality eyeglasses, earpieces, or even neural implants. So too, the advent of LLMs raises questions about the future value of some areas of learning -- will jobs in computer programming be supplanted the way that many jobs writing marketing content have been supplanted, for instance? The long-term impacts of generative AI on higher education remain uncertain.

Next steps for policymakers and institutional leaders

Based on this review, here are some recommended next steps for institutional leaders and policymakers hoping to bring learning analytics to a multi-campus university in Colombia.

Get the data ready. As discussed above, a first practical step is to undertake a systematic audit of existing data sources and infrastructure across all campuses, rather than assuming that “the data is there” and usable. Learning analytics initiative leaders should map which systems are in play on each campus (LMSs, student information systems, CRMs, library systems, survey tools, national exam databases), what level of granularity and historical depth they provide, and under what contractual conditions data can be accessed—renegotiating vendor agreements where necessary to secure fine-grained, event-level data and appropriate metadata. In a multi-campus Colombian university, this review will likely surface heterogeneity in legacy systems, local tools, and digitisation levels; part of "getting data ready" is deciding where to standardise and where to build translation layers so that analytics can compare patterns across regions and programmes without erasing local context. At the same time, institutions should invest in robust processes for linking data through privacy-preserving identifiers, establishing a secure, well-documented data warehouse or lake that can support both operational reporting and more advanced modelling. Finally, this technical work must be coupled with explicit assignment of data stewardship roles and clear data-quality processes, so that responsibility for defining fields, monitoring completeness and accuracy, and enforcing ethical access controls is clearly defined.

Get iterative design processes and implementation plans in place. Prior to beginning any algorithmic work, institutions should adopt explicit, cyclical design and implementation processes so that learning analytics emerges through testing, refinement, and scaling rather than a one-off deployment. Getting the right governance structure in place is also key to this aspect of the effort. This involves starting with clearly scoped pilots that address high-priority problems (such as dropout in first-year gateway courses) and embedding them in a deliberate cycle of analysis, co-design with instructors, advisors, and students, implementation, and evaluation. Decisions should be made about whether to pilot a single project on one campus, to pilot a single project simultaneously on multiple campuses, or to design different projects at different sites and compare the results. In any of these cases, there should be structured mechanisms for adapting initiatives for different campuses and programs, sharing adaptations, and identifying which design elements travel well across regions and which require local tailoring. Implementation plans should specify roles and responsibilities (including learning designers and implementation coordinators), timelines aligned with academic calendars, communication strategies, and criteria for success that include equity and unintended consequences alongside traditional performance indicators. By institutionalising these iterative processes—and documenting both successful and unsuccessful experiments—universities can build a repertoire of proven interventions, reduce the risk of large-scale failure, and cultivate a culture in which intervention plans are continually adjusted in response to evidence and lived experience rather than remaining static.

Get the right learning analytics expertise. Even with strong data infrastructure and thoughtful design processes, institutions are unlikely to achieve full impact without access to specialised expertise in learning analytics, data science, educational research, and implementation. Universities should therefore invest in building mixed teams that combine technical skills (for example, in data engineering, modelling, and dashboard design) with deep understanding of pedagogy, assessment, and student support, so that analytics work is anchored in educational questions rather than driven by whatever data happen to be available. It can be especially valuable to complement internal capacity with external consultants who have genuine, demonstrated experience in implementing learning analytics at scale— both algorithmic expertise in building models, and also in integrating them into institutional processes, navigating governance and ethics, and working with instructors and advisors. Such consultants can help avoid common pitfalls, provide tested design patterns for dashboards, alerts, and interventions, and offer independent critiques of proposed approaches, while also mentoring internal staff so that expertise is gradually localised rather than remaining permanently outsourced. Careful selection is critical: partners should be chosen for their track record of improving educational practice and outcomes, their willingness to engage with local constraints and equity concerns, and their commitment to transparent methods, rather than for generic "AI" branding or purely technical credentials.

Invest in data literacy, professional development, and implementation. To make learning analytics a sustained institutional practice rather than a one-off project, it is necessary to invest systematically in people as much as in tools. This involves coordinated data literacy initiatives for instructors, advisors, program directors, student-support staff, and leaders, with an emphasis not only on reading dashboards but on interpreting uncertainty, recognising the limits and biases of models, and combining quantitative indicators with local knowledge of students and programmes. Professional development should be embedded in existing structures, so that thinking with data becomes part of everyday practice across campuses rather than the preserve of a small analytics unit. At the same time, institutions should designate and provide resources for specialised roles, such as learning designers, data stewards, and implementation coordinators, who can bridge between technical teams and frontline educators, ensure that tools are aligned with curricular and equity goals, and support iterative cycles of piloting, feedback, and refinement in each regional campus and modality. Investing in these capacities also means allocating time in staff workloads for engagement with analytics—time to attend training, participate in co-design workshops, review evidence, and adjust courses or advising practices—rather than treating analytics work as an add-on. Finally, by recognising and rewarding effective use of analytics in promotion, evaluation, and institutional narratives of good practice, the university can signal that responsible engagement with data is a valued dimension of professional practice, helping to anchor learning analytics as a core component of its strategy for improving student success and equity across all campuses.

Center equity, ethics, and student agency. This article concludes with a reminder that is no doubt already clear to the leaders who commissioned this report -- in implementing learning analytics, we must always center the students. Centering equity, ethics, and student agency means treating learning analytics not only as a technical and organisational project, but as a commitment to the kinds of futures the institution wants to enable for its students. Analytics initiatives should be explicitly designed and evaluated in terms of their impacts on different student groups and campuses, with disaggregated evidence used to detect and address inequities linked to region, socio-economic background, race/ethnicity, disability, prior educational opportunity, and other factors. Ethical frameworks and governance structures need to move beyond compliance with regulations, articulating clear principles for what data will and will not be collected, how long it will be retained, how models will be validated, and how trade-offs between efficiency, fairness, and academic values will be handled. Ideally, student agency will be supported by practices that make analytics intelligible and contestable: students should know what data are being used about them, be able to understand and challenge inferences, and have genuine choices about whether and how they participate in analytics-supported interventions. This requires not only transparent communication, but also mechanisms—for example, advisory councils, student representation in governance bodies, and participatory design processes—through which students can shape priorities and raise concerns. By foregrounding equity, ethics, and agency in this way, the university can ensure that learning analytics strengthens, rather than undermines, its mission to widen opportunity, respect students as partners in their education, and uphold public trust in how data and AI are used in higher education. Ultimately, if these issues are attended to, learning analytics can achieve its potential and produce transformative benefits for students and their communities.

References

Adetutu, O. M., & Lawal, H. B. (2022). Applications of item response theory models to assess item properties and students'abilities in dichotomous responses items. Open Journal of Educational Development (ISSN: 2734-2050), 3(1), 01-19.

Alfredo, R., Echeverria, V., Zhao, L., Lawrence, L., Fan, J. X., Yan, L., ... & Martinez-Maldonado, R. (2024). Designing a human-centred learning analytics dashboard in-use. Journal of Learning Analytics, 11(3), 62-81.

Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive tutors: Lessons learned. The journal of the learning sciences, 4(2), 167-207.

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, 267–270.

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12) (pp. 267–270).

Arnold, K. E., & Pistilli, M. D. (2012, April). Course signals at Purdue: Using learning analytics to increase student success. In Proceedings of the 2nd international conference on learning analytics and knowledge (pp. 267-270).

Baker, R. S., & Siemens, G. (2013). Learning analytics and educational data mining: Towards communication and collaboration. Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, 252–254.

Baker, R., Lindrum, D., Lindrum, M.J., Perkowski, D. (2015) Analyzing Early At-Risk Factors in Higher Education e-Learning Courses. Proceedings of the 8th International Conference on Educational Data Mining, 150-155.

Baker, R.S. (2025) Big Data and Education. 9th Edition. Philadelphia, PA: University of Pennsylvania.

Baker, R.S., Gowda, S.M., Salamin, E. (2018) Modeling the Learning That Takes Place Between Online Assessments. Proceedings of the 26th International Conference on Computers in Education, 21-28.

Baker, R.S., Liu, X., Shah, M., Pankiewicz, M., Kim, Y.J., Lee, Y., Porter, C. (in press) Generative AI as a Teaching Assistant. To appear in Vincent-Lancrin (Ed.) OECD Digital Education Outlook 2026.

Baker, R.S., Wagner, A.Z., Corbett, A.T., Koedinger, K.R. (2004) The Social Role of Technical Personnel in the Deployment of Intelligent Tutoring Systems. CMU Technical Report CMU-HCII-04-100, July 2004.

Baker, R.S.J.d., Ocumpaugh, J. (2014) Interaction-Based Affect Detection in Educational Software. In R.A. Calvo, S.K. D'Mello, J. Gratch, A. Kappas (Eds.), The Oxford Handbook of Affective Computing. Oxford, UK: Oxford University Press.

Baker, R.S.J.d., Yacef, K. (2009) The State of Educational Data Mining in 2009: A Review and Future Visions. Journal of Educational Data Mining, 1 (1), 3-17.

Bodily, R., Kay, J., Aleven, V., Jivet, I., Davis, D., Xhakaj, F., & Verbert, K. (2018, March). Open learner models and learning analytics dashboards: a systematic review. In Proceedings of the 8th international conference on learning analytics and knowledge (pp. 41-50).

Bradberry, C., Ray, A., Wayman, M., Dhami, J., Charnock, J., & Pittges, J. (2017). Explaining and Predicting First Year Student Retention via Card Swipe Systems. Proceedings of the International Conference on Semantics, Ontologies, Intelligence and Intelligent Systems (SIGODIS).

Brown, A., Basson, M., Axelsen, M., Redmond, P., & Lawrence, J. (2023). Empirical evidence to support a nudge intervention for increasing online engagement in higher education. Education Sciences, 13(2), 145.

Buckingham Shum, S., & Shibani, A. (2019). Learning Analytics Growing Pains–Socio-technical Infrastructure Changes as LA Tools Mature. Australian Learning Analytics Summer Institute.

Calo, T., & Maclellan, C. (2024, July). Towards educator-driven tutor authoring: generative AI approaches for creating intelligent tutor interfaces. In Proceedings of the Eleventh ACM Conference on Learning@ Scale (pp. 305-309).

Campbell, J. P., DeBlois, P. B., & Oblinger, D. G. (2007). Academic analytics: A new tool for a new era. EDUCAUSE Review, 42(4), 40–57.

Cosyn, E., Uzun, H., Doble, C., & Matayoshi, J. (2021). A practical perspective on knowledge space theory: ALEKS and its data. Journal of Mathematical Psychology, 101, 102512.

Esbenshade, L., Baker, R. S., & Vitale, J. (2023, June). From a prediction model to meaningful reports in school. In Education Leadership Data Analytics (ELDA) 2023 Conference (New York, NY.)

Feng, M., & Heffernan, N. T. (2006). Informing teachers live about student learning: Reporting in the assistment system. Technology Instruction Cognition and Learning, 3(1/2), 63.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. TechTrends, 59(1), 64–71.

Google (2025) AI tutoring can safely and effectively support students: An exploratory RCT in UK classrooms. https://storage.googleapis.com/deepmind-media/LearnLM/learnLM_nov25.pdf

Hooshyar, D., Tammets, K., Ley, T., Aus, K., & Kollom, K. (2023). Learning analytics in supporting student agency: A systematic review. Sustainability, 15(18), 13662.

Iraj, H., Fudge, A., Khan, H., Faulkner, M., Pardo, A., & Kovanovic, V. (2021). Narrowing the Feedback Gap: Examining Student Engagement with Personalized and Actionable Feedback Messages. Journal of Learning Analytics, 8(3), 101-116.

Jayaprakash, S. M., Moody, E. W., Lauría, E. J. M., Regan, J. R., & Baron, J. D. (2014). Early alert of academically at-risk students: An open source analytics initiative. Journal of Learning Analytics, 1(1), 6–47.

Ju, S., Zhou, G., Barnes, T., & Chi, M. (2020). Pick the Moment: Identifying Critical Pedagogical Decisions Using Long-Short Term Rewards. Proceedings of the International Conference on Educational Data Mining.

Kaliisa, R., Misiejuk, K., López-Pernas, S., Khalil, M., & Saqr, M. (2024, March). Have learning analytics dashboards lived up to the hype? A systematic review of impact on students' achievement, motivation, participation and attitude. In Proceedings of the 14th learning analytics and knowledge conference (pp. 295-304).

Khachatryan, G. A. (2020). Instruction modeling: Developing and implementing blended learning programs. Oxford University Press.

Khalil, M., & Ebner, M. (2016). De-identification in learning analytics. Journal of Learning Analytics, 3(1), 129-138.

Khosravi, H., Shabaninejad, S., Bakharia, A., Sadiq, S., Indulska, M., & Gasevic, D. (2021). Intelligent Learning Analytics Dashboards: Automated Drill-Down Recommendations to Support Teacher Data Exploration. Journal of Learning Analytics, 8(3), 133-154.

Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y. S., Kay, J., ... & Gašević, D. (2022). Explainable artificial intelligence in education. Computers and education: artificial intelligence, 3, 100074.

Koedel, C., & Rockoff, J. E. (2015). Value-added modeling: A review. Economics of Education Review, 47, 180-195.

Krumm, A., Means, B., & Bienkowski, M. (2018). Learning analytics goes to school: A collaborative approach to improving education. Routledge.

Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: a meta-analytic review. Review of educational research, 86(1), 42-78.

Kyte, S. B., Atkins, C., Collins, E., & Deil-Amen, R. (2023). Understanding the impact of data-driven tools on advising practice and student support. Journal of Postsecondary Student Success, 2(4), 63–82.

Lee, D., Arnold, M., Srivastava, A., Plastow, K., Strelan, P., Ploeckl, F., ... & Palmer, E. (2024). The impact of generative AI on higher education learning and teaching: A study of educators' perspectives. Computers and Education: Artificial Intelligence, 6, 100221.

Lin, J., Rao, J., Zhao, Y., Wang, Y., Gurung, A., Barany, A., Ocumpaugh, J., Baker, R.S., Koedinger, K.R. (2025) Automatic Large Language Models Creation of Interactive Learning Lessons. Proceedings of the 20th European Conference on Technology Enhanced Learning.

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

Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. EDUCAUSE Review, 46(5), 31–40.

Milliron, M. D., Malcolm, L., & Kil, D. (2014). Insight and Action Analytics: Three Case Studies to Consider. Research & Practice in Assessment, 9, 70-89.

Molenaar, I., Horvers, A., Dijkstra, R., Baker, R. (2019) Designing Dashboards to Support Learners' Self-Regulated Learning. Companion Proceedings of the 9th International Learning Analytics and Knowledge Conference.

Murray, T., Blessing, S., & Ainsworth, S. (Eds.). (2013). Authoring tools for advanced technology learning environments: Toward cost-effective adaptive, interactive and intelligent educational software. Springer Science & Business Media.

Outerbridge, S., & Taub, M. (2025, March). Towards a Teacher-and Student-Facing Dashboard to Scaffold SRL and Motivation for Improved Learning Outcomes. In Society for Information Technology & Teacher Education International Conference (pp. 2864-2870). Association for the Advancement of Computing in Education (AACE).

Pankiewicz, M., Baker, R.S. (2023) Large Language Models (GPT) for automating feedback on programming assignments. Proceedings of the 31st International Conference on Computers in Education.

Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. British journal of educational technology, 45(3), 438-450.

Pelánek, R. (2017). Bayesian knowledge tracing, logistic models, and beyond: an overview of learner modeling techniques. User modeling and user-adapted interaction, 27(3), 313-350.

Poquet, O., Kitto, K., Jovanovic, J., Dawson, S., Siemens, G., & Markauskaite, L. (2021). Transitions through lifelong learning: Implications for learning analytics. Computers and Education: Artificial Intelligence, 2, 100039.

Queiroga, E. M., Batista Machado, M. F., Paragarino, V. R., Primo, T. T., & Cechinel, C. (2022). Early prediction of at-risk students in secondary education: A countrywide K-12 learning analytics initiative in Uruguay. Information, 13(9), 401.

Rose, D. (2000). Universal design for learning. Journal of Special Education Technology, 15(4), 47-51.

Rust, M. M., & Motz, B. A. (2025). Incorporating an LMS learning analytic into proactive advising: Validity and use in a randomized experiment. The Internet and Higher Education, 101057.

Saqr, M., & López-Pernas, S. (2024). Learning analytics methods and tutorials: A practical guide using R (p. 736). Springer Nature.

Sclater, N., Peasgood, A., & Mullan, J. (2016). Learning analytics in higher education: A review of UK and international practice. Jisc.

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. American Behavioral Scientist, 57(10), 1510-1529.

Smolansky, A., Cram, A., Raduescu, C., Zeivots, S., Huber, E., & Kizilcec, R. F. (2023, July). Educator and student perspectives on the impact of generative AI on assessments in higher education. In Proceedings of the tenth ACM conference on Learning@ Scale (pp. 378-382).

Stahl, M., Biermann, L., Nehring, A., & Wachsmuth, H. (2024, June). Exploring LLM Prompting Strategies for Joint Essay Scoring and Feedback Generation. In Proceedings of the 19th Workshop on Innovative Use of NLP for Building Educational Applications (BEA 2024) (pp. 283-298).

Stavrinides, P., & Zuev, K. M. (2023). Course-prerequisite networks for analyzing and understanding academic curricula. Applied Network Science, 8(1), 19.

Susnjak, T. (2024). Beyond predictive learning analytics modelling and onto explainable artificial intelligence with prescriptive analytics and ChatGPT. International Journal of Artificial Intelligence in Education, 34(2), 452-482.

Verbert, K., Ochoa, X., De Croon, R., Dourado, R. A., & De Laet, T. (2020, March). Learning analytics dashboards: The past, the present and the future. In Proceedings of the tenth international conference on learning analytics & knowledge (pp. 35-40).

Volkwein, J. F. (1999). The foundations and evolution of institutional research. New Directions for Institutional Research, 1999(104), 5–20.

Weil, D., Kendall, C., & Snyder, R. (2023). A modern framework for institutional analytics. EDUCAUSE Review.

Yu, R., Pardos, Z., Chau, H., & Brusilovsky, P. (2021, June). Orienting students to course recommendations using three types of explanation. In Adjunct proceedings of the 29th ACM conference on user modeling, adaptation and personalization (pp. 238-245).