Learning Analytics and Big Data to Generate Early Alerts

Introduction

Learning analytics plays a key role in the improvement and personalization of education. Students desire real-time feedback as they learn, and believe analytics positively impacts their academic performance, but transparency and communication are vital to the success of a learning analytics initiative (Boyer & Bonnin, 2016). Current research provides a solid foundation for higher education institutions to consider implementing a learning analytics framework, but strongly suggests doing so with caution. The purpose of this report is to provide a broad review of the research pertaining to implementation considerations for an early alerts system.

Influencers in Adoption of Predictive Models

As institutions and their student populations evolve, so should the analytics system to remain sustainable, relevant, and accurate; therefore, evaluation is required (Villano et. al., 2018). The selected system must create a cultural change and reinforce students as agents of their own learning. The following are identified as key stakeholders and important influencers in the adoption of an early alert system.

* University leadership– Implementing an early alert system requires strong public support by senior leadership (Villano et. al., 2018).
* Faculty/Advisors/Students – Participation by the campus community is vital to the program’s success. To increase buy-in, communicate and involve these key stakeholders early in the process and provide continuous updates connecting their contributions to the impact on the program.
* User Experience – The model must be perceived as effective and easy to use by anyone, student, educator, or decision maker. Additional information on this topic is included in the dashboard section below.
* Objectives – JMU identified the purpose of implementing an early alert system as improving retention and closing the retention equity gaps. Establishing such a focused objective is vital to implementing an early alert program.
* Intervention Pathways – A clear link between early alerts and suggested interventions are essential.

Data Sources

Developing algorithms for a predictive learning model is a complex endeavor and one that is unique to each university, so no two systems are the same. The complexity of code is dependent upon the objectives, available hardware and software and user experience. Research identifies three areas of data most used in predictive learning analysis including static, activity and achievement data (Alhadad et. al., 2015). However, it is imperative that students are informed of what data is collected and how it is being used, as well as establishing data governance policies and processes for managing that data.

* Activity Data is considered the most significant predictor of student success.
* Learning management system – LMS data examples include total login frequency, course absences, time spent in the system, number of downloads, interactions with peers, number of exercises performed, number of forum posts, duration of engagement with materials in the system, and assignment grades (Dietz-Uhler & Hurn, 2013, Mwalubwe & Mtebe, 2017).
* Library systems and e-Textbooks – Newly identified contributors to learning analytics includes login frequencies, downloads, time spent within these systems, books checked out, and study rooms reserved (Oakleaf et. al., 2017).
* Achievement Data
* Assignment/Mid-term grades – Student achievement data includes college level course completion rates, assignment grades and mid-term grades (Swaak, 2022).
* Static Data is beneficial but is considered the least effective predictor of student success (Sclater et. al., 2016).
* Past academic performances – Past academic performances is a contributing factor when considering college level coursework.
* Student survey data – Annual student survey data is included in many early-alert systems (Johnson et. al., 2012).
* Student Information Systems – Data including courses undertaken, residency on-campus or off, and demographics with caution (Villano et. al., 2018).

Dashboards

Institutions implementing a learning analytics initiative must consider the specific tools and accesses needed to collect, store, and analyze data as well as a dashboard to visualize the information in meaningful ways (Mah, 2015). Developing an effective dashboard design means considering factors beyond simple user and interface with the goal of providing cognitive and behavioral process-oriented feedback to learners and educators to initiate positive change (Sedrakyan et. al., 2018). Beyond technical capabilities, the designing team must understand the cognitive cues associated with data visualization, design best practices, as well as contain domain expertise in learning theories and paradigms (Susnjak et. al., 2022). The visualization technique needs to ensure the design is aesthetically pleasing, providing information in meaningful ways while not overwhelming the user (Susnjak et. al., 2022). The platform must provide the learner with a clear understanding of the link between the data and the recommended intervention, and an opportunity to either opt-in or out of the systems empowering students with control over how their data is being used (Villano et. al., 2018). Users must accept and understand the information provided in order to take the appropriate action and ensure a successful outcome. The goal is to transform data into knowledge.

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