OEA Student Attrition

Use Case Defined

August 2023

This Use Case for a Predictive Model of Student Attrition was developed through a work by Microsoft Education, Kwantum Analytics, and Broward College in Broward County, Florida.

1) The Use Case Problem

Defining the Problem: What problem does this use case seek to solve?

Broward College in Florida caters to a diverse student population of over 55,000 individuals, many of whom are first-generation college students or eligible for federal Pell Grants. The college takes pride in accepting every student and is committed to meeting their unique needs and challenges. Whether pursuing full-time degree programs or part-time certificates, each student comes with their own educational and career ambitions. To address the issue of student attrition, Broward College turned to data-driven solutions, aiming to decrease the rate at which students withdraw or leave before completing their course plans.

Broward College utilized Azure Machine Learning to identify five critical factors that predict student attrition: cumulative credit hours earned, cumulative GPA, high school degree and/or GED status, and course modality (in-person, blended, or online learning). Armed with these predictors, the college is now implementing data-driven student support strategies campus-wide and modifying course design, scheduling, and learning methods accordingly. The use of machine learning has significantly expedited data processing, enabling the team to swiftly respond to students' needs and isolate potential confounding variables, such as the impact of the pandemic on student retention.

With the actionable insights generated from machine learning, Broward College offers tailored and proactive interventions to support each student based on their specific requirements. For instance, through the "Take One More" campaign, students nearing the threshold of cumulative credit hours are encouraged to add another class, as this has been found to increase their chances of success. Broward College is committed to helping students complete their education successfully, using technology to predict and provide assistance, thus ensuring students' progress along their educational pathways.

2) The Use Case Stakeholders

Who are the stakeholder groups for this use case, and how are they involved in its development?

Education system teams responsible for addressing student attrition can collaborate with technology and data groups in the system and external education analytics companies to develop a predictive model that identify key factors of student attrition and highlight students' relationships to those key factors. To build an informed, ethical, and effective use case, many stakeholder groups should be involved in the design and development of the use case.

Stakeholder Groups	Relationship to Use Case	Involvement in Use Case
Students	***Indirect:*** *providers of data to the predictive model, and ultimately receive preventative solutions if they fall in high-risk categories.* *They or their families or guardians should have awareness and give permission for their data to be used.*	*In the initial phases of model development and intervention designs, various types of students should be consulted in the model design process (review of data sources used, theory development). At a later stage, students identified as at-risk will receive or participate in intervention solutions and provide feedback to the system.*
Parents or Guardians	***Indirect:*** *May be providers of data to the predictive model, and ultimately receive preventative solutions if they fall in high-risk categories.* *Families or guardians should have awareness and give permission for students' data to be used.*	*In the initial phases of model development and intervention designs, parents or guardians should be involved in the model design process (review of data sources used, theory development). At a later stage, families identified as having at-risk students may receive or participate in intervention solutions and provide feedback to the system.*
Educators (Faculty or Teachers) and School Support Staff	***Indirect:*** *May participate in developing and implementing preventative solutions.*	*Educators may directly provide data or feedback to the model and utilize data or insights if they are part of an intervention to prevent student attrition.*
School or Department Leaders	***Indirect:*** *participate in developing and implementing preventative solutions.*	*Leaders would directly utilize a data tool that reliably identifies students' relationships to key factors of student attrition.*
School System or Institutional Leaders	***Direct:*** *responsible for addressing student attrition in schools.*	*Will lead efforts to develop the model and implement preventative solutions.*
Researchers	***Direct:*** *research student attrition patterns in the system and be key partner in developing the model.*	*Responsible for maintaining and updating the system to ensure ongoing accuracy of the predictive model.*
Potential Malicious Actors	***Indirect:*** *Student hackers, external hackers.*	*Corrupt data sources or modify predictive model so the model does not accurately predict at risk students. Act to misuse intervention solutions.*

Outline how stakeholders will be involved in the development in different stages of the use case development:

Early Stages: Defining the use case problem, developing the local theory or conceptual model of the problem, identifying key data sources to include in the use case in the local context:

Students, families or guardians, educators, school leaders, system leaders and researchers: In the initial phases of model development and intervention designs, these stakeholders will be involved in the model design process by providing their perspectives on causes of student attrition in the local context (theory development), and in reviewing the data sources that are intended to be used in model development, for example to provide input on the quality and applicability of those data sources to the use case.

Focus group discussions should take place with these groups to assess their interest, concerns and ideas about this model development and the potential intervention solutions that might be valuable for the education system to provide to evaluate Student Attrition.

Reviewing and Designing Outputs Stages: Testing validity of the use case results, developing dashboard designs or set of interventions based on the use case results:

As the predictive model is developed, these same stakeholders will again review the model and check for transparency, accountability, and ask other questions or concerns around how the model addresses responsible AI principles (see below). In addition, they will be asked for input on 1) how the model outputs should be communicated (e.g., dashboard designs) and 2) the set of interventions developed to address Student Attrition and whether some of these interventions can or should be automated. Finally, when the model starts to be used, they should provide continuous feedback on the system, correcting the model over time.

What type of outputs are expected from this use case, such as AI models, dashboards, or notification systems?

Stakeholder Group	**Outputs**
Students	*Depending on the output results, students may receive interventions such as support groups, medical or mental health supports, transportation assistance, dependent on the individual's key factors.*
Parents or Guardians	*Depending on the output results, families of students may receive interventions such as support groups, medical or mental health supports, transportation assistance, dependent on the individual's key factors.*
Educators (Faculty or Teachers) and School Support Staff	*Depending on the output results, educators may have access to a tool, dashboard, or data set that identifies students in their current classes, the factors that may affect students, and recommends a specific intervention or provides intervention suggestions to the educator to choose among.*
School or Institution Leaders	*Depending on the output results, leaders may have access to a tool, dashboard, or data set that identifies students in their schools and recommends a specific intervention or provides intervention suggestions for students.*
System Leaders	*Data analysis and exploration dashboards to understand patterns attributing to student attrition, changes in key factors of student attrition over time, and analysis of the impact of interventions towards student attrition.*

3) Mapping Theory to Data

For this use case, what prior research or conceptual model frames your theory of the problem?

Mapping Theory to Data. From prior research or conceptual models what are the key data categories expected to inform this use case? What local data sources are available or needed for each category? Please note where no data is available for a Data Category

A key part of the use case development process is deciding which data to use and how it should be mapped to the theory of the problem. Identifying which data should be viewed as a "feature" and which data is the "target outcome" is at the core of this mapping.

Note: OEA modules can provide data sources that support the student attrition use case through accelerating the ingestion of key data sources needed and providing resources to set up these use cases.

Note: Mapping theory to data with a 'data dictionary.'

A "data dictionary" allows the data team to examine specific data tables and data entities in the available datasets, and then map specific items to the Key Data Category.

New data services like Azure Purview can support this work through creating a holistic, up-to-date map of a data repository with automated data discovery, sensitive data classification, and end-to-end data lineage.

Please see "Privacy and Security" section below for more ensuring that sensitive data is protected.

4) Responsible AI Principles Applied

In these next sections, please answer the questions under each of the headings describing how responsible AI principles will be applied to this use case.

Fairness Principle

Who is most likely to be at risk of experiencing harm from this use case?

"Harm" can be subjective. Children from low-income families and/or children in traditionally underserved student groups (student with disabilities, English language learners, youth involved in the juvenile justice system) typically have higher incidences of attrition and therefore are deserving of additional support. On the other hand, parents and community leaders representing low-income and/or traditionally underserved student populations are extremely sensitive to systems that profile and/or track students and are not easily convinced that such systems are in the best interests of their children.

Parents and community leaders can also be highly skeptical of systems that are not easily explainable.

Potential harms include:

- Removing a teacher from a specific post (based on false or misleading information)
- Supports for a student withheld (in false negative)
- Misdiagnosing causes of student attrition – and then providing them with the wrong or inappropriate support.

Planned Mitigations:

- Involve stakeholders from each of the groups in the early planning, design, development and testing of the model and interventions and use their input to design the system for their needs
- Pilot slowly and iteratively test to build shared understanding of the system and improve accuracy of predictive model
- Build feedback loop into system for student, teacher, and all stakeholders in the system.

Reliability and Safety Principle

Systems should operate reliably and safely when they function in the world. AI systems must be designed with a view to the potential benefits and risks to different stakeholders and undergo rigorous testing to ensure they respond safely to unanticipated situations and do not evolve in ways that are inconsistent with the original shared purpose.

What are possible risks faced by learners or educators from the analytics of this use case?

A second risk factor is model disparity in relation to student demographics. Even though demographic data such as gender or race are not included in the model building process, the model may interpret demographic separations indirectly through other variables such as income level or exam scores. Because of this, the model may perform better for some demographic groups than others. This principle is known as "model fairness."

Planned Mitigations:

To protect against a model performing better for some groups of students compared to others, 2 key strategies need to be incorporated.

1. *Monitoring* of model performance across different groups of students is needed. This can be done with a basic PowerBI dashboard. It is essential that any model performs fairly for all demographic groups. For target prediction of student attrition, it may be useful for stakeholders to want to model to perform most accurately on actionable student groups such as students who are most at-risk.
2. *Retraining* models which perform unfairly. Two approaches here include balancing training data across demographic groups of concern (i.e., Fairlearn) and building complex enough models (such as ensembles) which are rigorously tested via cross validation practices.

Transparency Principle

Transparency requires visibility into all levels of decision-making and design of an AI system. Designers should clearly document their goals, definitions, and design choices, and any assumptions they have made. Those who build and use AI systems should be forthcoming about when, why, and how they choose to build and deploy them, as well as their data and systems' limitations. Information should be readily available on the quality of the predictions and recommendations the AI system makes. Transparency also encompasses intelligibility, which means that people (in this case, educators, parents, students, etc.) should be able to understand, monitor, and respond to the technical behavior or recommendations of AI systems.

What steps will the analytics or AI process include?

The AI process is outlined in 4 main steps:

1. *Data subsetting and aggregation:* Data identified in the above theory and data discussion will be located in the production data environment. Only the columns needed for model building will be used.

2. *Feature engineering and model table construction:* Data from step 1 will be combined into a single table for building the predictive model. Because each row in this table represents 1 student's data, certain columns such as attendance records will need to be aggregated into a single metric.
3. *Model building:* AutoML will be used to build a best performing model via Azure Machine Learning Studio. This process will record and catalog the model table and all models produced for future reference. The model will be used to make predictions on the model table and InterpretML will be used to identify individual feature importance.
4. *PowerBI deployment*: Model results and other data (i.e., SIS/MIS, time dependent attendance, demographics) will be made queryable by a PowerBI dashboard. This dashboard will be used to explore model findings and assess fairness.

Who will develop the analytics or models?

In the Broward College predictive modelling work, Kwantum Analytics developed the primary predictive model.

How will the limitations of the analytics or AI model be communicated to stakeholders and users?

Training should be conducted for all users and stakeholders of the Student Attrition model, including training on the limitations and weaknesses of the model. Training should include guidance on how they can use the system to inform interventions or actions taken with students, but that the system should be used to inform their decisions, not make their decisions. If the end user's judgement of a student's situation does not match the system's data, the end user should be trained to provide feedback to better train the model, or at least question the data being presented.

What means will be built into the system for correction and model feedback by those who provide data and who use its outputs?

As part of the above training, users of the model:

1) Should provide feedback or additional inputs to the system (such as tagging which interventions or activities were taken)
2) Should provide feedback to the system if the data or recommendations were incorrect or questionable given the user's knowledge of the student and their context.

Privacy and Security

Private or personal data should not be collected or incorporated in analytics or AI products for education unless all groups have agreed this data is necessary to achieve the shared purpose of a specific analytics or AI project. Additionally, the people providing the data need to give permission for the data to be used for this purpose, such as through school policy at enrollment. Ideally, data providers should directly understand the value that they will receive as a result of sharing their data. Finally, the security of that data must be protected, guidelines or policies developed for which roles can access which data, and the level of anonymization needed for specific use case purposes defined.

Identifying sensitive data, such as personal information, should be part of the use case process. In OEA modules for individual datasets, sensitive data is often pre-identified, and scripts are written to pseudonymize or anonymize specific data fields before they "land" in Stage 2 data lakes and are accessed by researchers or data scientists. For datasets that are not OEA modules, the process of identifying data for sensitivity classification should be conducted through a collaboration between the project's data engineers and individuals who understand the local education context and datasets.

How will access to sensitive data be secured and protected in the data environment?

Only pseudonymized student data will be used to build and assess models, so no students will be available or identified through this process. If the school system wishes to re-identify students (so that supports can be provided to the student), re-identifying the student data will be performed only by those inside the education system with appropriate role-based permissions governed through the above policies and implemented through Azure Active Directory.

Accountability

Accountability requires that people who develop and deploy AI systems be held responsible for how they operate. AI systems should never be left to operate unchecked, irrespective of the degree to which they may be capable of acting autonomously. This is what is meant by the phrase "humans in the loop." A part of this is ensuring documentation of the decisions made during the AI system development. This document can be used for that purpose.

Who is responsible for reviewing the Use Case documentation and ensuring that the implementation meets responsible AI principles?

The decision makers in the education system who use the predictive model in practice to identify supports for students and schools will be responsible for continued implementation of the principles responsible AI described in this document. They should review this documentation thoroughly and update it if decisions or data changes.

How will stakeholders and end users be trained on the appropriate use of the system?

Kwantum Analytics will train key data stakeholders on interpretations of model accuracies via deployed PowerBI dashboards. Detailed technical documentation will be created as a reference.

Education system leaders and schools will be responsible for training schools, educators, and all support staff and stakeholders on how to understand the model, dashboards and other outputs from the model, and on the appropriate and intended use of the outputs to inform their decisions and actions at the school and student level.

How will the analytics or AI system be monitored over time to ensure analytics and prediction perform reliably? Who will be responsible for this?

Kwantum Analytics will be responsible for monitoring analytics and prediction performance during the initial stages of this work. Through communications with education system leaders responsible for the model, an accuracy threshold (i.e., 80% accurate) will be determined to decide if model quality is sufficient for use in practice. Model accuracy should be checked quarterly with the use of new attendance record data. It is recommended that the model be retrained every 1-2 years by either the education system's data scientists or an external data science partner.

Inclusion

The datasets used in learning analytics and AI determine the insights and predictions produced. If those datasets do not represent the whole population of learners, if the data quality is poor, or if certain types of data are not included in the models, it will decrease the accuracy, validity, and inclusiveness of the insights. Similarly, if the way the insights are acted upon by the system do not include all groups (e.g., students with disabilities), it can reinforce exclusion from learning opportunities.

What are the constraints of these local data sources for this specific use case?

Please describe the limitations of these datasets. For example, are the datasets missing data for certain student populations? Is there bias in the data collection method?