Uncovering Opportunities for Support: A Gap Analysis of Integrated Systems in Assisting PA Students at Risk of Academic Failure

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Abstract

Physician Assistant (PA) graduate programs face significant challenges in identifying and supporting students at risk of academic failure. With rising demands in healthcare education and the need for competent healthcare providers, particularly in marginalized communities, the effective support of PA students is crucial. This study aims to explore and develop an integrated data strategy to support the early identification and intervention of students at risk of academic failure in the Physician Assistant Graduate Institute (PAGI) program. The research focuses on leveraging existing technical infrastructures and enhancing data governance to facilitate targeted and effective student support. Utilizing a combination of document reviews, system explorations, and interviews, the study examines current data collection and communication methods within PAGI's program. This includes an in-depth analysis of admissions data, probationary student academic data, program goals, and feedback from key programmatic individuals. The research highlights the underutilization of available data in existing systems, such as the Learning Management System (LMS) and Student Information System (SIS), for early identification of at-risk students. It reveals a need for improved data governance, enhanced communication pathways among stakeholders, and strategic use of data for proactive student support. Implementing an integrated data strategy with robust governance can significantly improve the identification and support of at-risk students in PA programs. Enhancing data utilization and communication can lead to more informed decision-making, tailored interventions, and improved student outcomes.

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A physician assistant graduate education program represents a specific strategy and operational principles governing its decision-making and practice model. This means that the education program for physician assistants has a clear plan for educating and training its students. This could relate to the curriculum, teaching methods, clinical training, or other educational objectives. The program's operational principles are the practices that guide the program's daily operations. They dictate how courses are taught, how students are evaluated, and how the program interacts with its students, faculty, and other stakeholders. The strategy and operational principles influence and direct how the program makes decisions about its curriculum, teaching methods, and other aspects, as well as how it trains its students to practice as physician assistants.

In the United States, the Accreditation Review Commission on Education for the Physician Assistant (ARC-PA) is the accrediting agency that sets standards for physician assistant (PA) education. The ARC-PA ensures PA programs have a clear educational strategy, including a well-defined curriculum that aligns with ARC-PA standards. The PA program's specific strategy and operational principles–policies, procedures, and practices–must ensure that students receive comprehensive training in medical knowledge, clinical skills, and professional behavior to meet the ARC-PA standards. To meet accreditation standards, such strategies and principles should include student evaluation methods that support decision-making and practice models.

Within standards C1.03 and E1.03, ARC-PA identifies the need for programs to demonstrate the relationship between student behavior, student support services, and student outcomes. Program operating principles should include an emphasis on consistent documentation and critical data analysis supporting the ability to link analysis to data-driven conclusions, facilitating data-driven decision-making, and subsequent identification of program strengths, modifications, and areas needing improvement.

PA program leadership is responsible for being mindful of issues impacting student success and recognizing the importance of change in supporting an environment in which students can achieve identified outcomes as a critical priority. Therefore, recognizing the key variables linked to student success within the program serves as a first step in supporting the desired outcomes. To understand whether a program's strategy and principles enable an effective practice model, proper benchmarking for strengths of the operational tenets should communicate clear criteria for academic performance, early warning systems to detect students at risk, and remediation plans to support them.

A well-defined data strategy provides PA programs with a robust framework for monitoring, assessing, and improving their students' academic journey. By leveraging data-driven insights, these programs can identify early indicators of academic challenges, tailor interventions to individual student needs, and adapt curricular and instructional strategies to meet evolving educational standards. In an era where data is increasingly recognized as a critical asset in education, PA programs that effectively utilize data enhance their academic offerings and significantly contribute to the preparedness and success of their graduates in the demanding healthcare sector.

A data strategy that supports student academic achievement within a graduate PA program involves several key components (Hosch, 2019). Each component plays a vital role in ensuring that the data collected is relevant, insightful, and actionable.

1. Data Collection: Relevant data might include academic performance, attendance records, engagement metrics, clinical performance evaluations, and potentially non-academic indicators like student wellness and socio-economic factors.
2. Data Integration: It is essential to cohesively integrate data from various sources like learning management systems, student information systems, and external sources.

3. Data Analysis and Interpretation: Predictive analytics helps identify patterns and trends, such as risk factors for academic probation.
4. Actionable Insights: A data strategy's objective is to use the insights gained to inform decision-making. This could involve identifying students who need additional support, modifying the curriculum based on student performance trends, or making administrative changes. The decisions should be evidence-based and aimed at improving student academic outcomes.
5. Continuous Monitoring: A dynamic data strategy involves establishing feedback loops where outcomes of interventions are assessed, and the strategy is adjusted accordingly.

It is important to note that while it is critical for programs to focus on support for all students, independent of their backgrounds, programs that focus on supporting students from historically marginalized communities have additional challenges. A comprehensive strategy necessitates an emphasis on understanding and supporting the entire trajectory of HM students throughout their PA education journey, ensuring their persistence and success in graduating from their programs. A cautionary flag regarding the failures of HM students to meet academic standards is provided by a 2019 study that shows HM students are dismissed from PA programs for academic reasons at a greater rate than their White peers (Chitwood et al., 2019).

A PA graduate program is not merely an institution for learning; it embodies a distinct strategy and a set of operational principles that steer its decision-making processes and overall practice model. These foundational elements are pivotal in shaping students' educational experiences and ensuring their success. However, as the landscape of PA education evolves and the challenges faced by students become more multifaceted, a pressing need arises to evaluate the alignment of these strategies and principles with the realities impacting student achievement. PA programs need to identify the resources available to key stakeholders to determine where weaknesses exist to address these challenges and improve performance successfully.

Purpose of the Study

In 2021, the Physician Assistant Graduate Institute (PAGI) was placed on accreditation-probation status, indicating the program does not, in the judgment of the ARC-PA, meet the standards or the capability to provide an acceptable educational experience for its students (ARC-PA, 2023). Over the past three student cohorts, PAGI has experienced a dramatic rise (200%) in the number of students meeting the threshold for placement on academic probation. In the ARC-PA program evaluation documents, PAGI was found to have insufficient data collection and analysis to support understanding of student attrition and achievement of desired outcomes. In addition, the program had failed to articulate specific benchmarks to determine the strength of current practices to support desired educational outcomes. So, while the program continues to experience a rise in poor student academic outcomes, as determined by required remediation rates, the program does not have the proper mechanisms to understand why the phenomenon occurs.

Central to this study is an examination of the existing use of data within PAGI. Program leadership communicates a notable lack of a systematic approach to data collection and analysis (A. Brown, personal communication, August 18, 2023, a deficiency that this study intends to scrutinize. This absence is significant, given the potential of data-driven strategies to identify students at risk of academic difficulties early in their academic careers.

This study looks at the phenomena within the PAGI Master of Science program to understand how the PA program frames its retention strategy for students. It investigates how its current systems can provide faculty and staff comprehensive insight into evidence-based positive and negative student academic achievement predictors. Additionally, it leverages the existing research to identify the known academic and non-academic predictors[1] of academic achievement. It evaluates how PAGI's current admissions, advising, and academic remediation processes address those predictors in their delivery of student support. The aim is not to verify the predictors but instead to evaluate how such predictors are identified, captured, and communicated during the admissions process and the first year of didactic coursework.

In addition, this study investigates information sharing during the admissions, coursework, and remediation processes to support improved student academic performance. Acknowledging the importance of a seamless flow of information between critical stages of a student's journey, the aim is to identify current opportunities for exchanging insights and developing feedback loops to facilitate continuous student support efforts.

The outcome of this study will provide a recommended coordinated approach to sharing information for timely and proactive intervention as well as continuous improvement of data collection and analysis functions related to student success.

Context of the Study

The Physician Assistant Graduate Institute (PAGI) is one of the 303 PA programs within the U.S. accredited by the ARC-PA. While the program supports all students interested in the PA profession, it aims to improve the number of HM PAs within the healthcare community by admitting students from HMCs to educate, train, and graduate culturally competent professionals who will practice in underserved communities. Like other PA programs, PAGI seeks to engage in activities that expand quality and equitable care to a diverse population of patients. The program's mission is driven by the

[1] Research findings focused on identifying predictors of academic achievement use both the terms "academic" and "cognitive" to discuss academic performance factors. As cognition expands beyond the quantitative achievements and encompasses abilities such as problem-solving, critical thinking, and reasoning, this study uses the term academic, instead of cognitive, to refer to predictors specifically related to measuring and identifying academic achievement.

increasing healthcare inequities experienced by vulnerable populations, and therefore, the program's goals focus on improving the academic performance of its predominantly HM students.

Each year the program admits three cohorts of 30-50 students. While the program successfully achieves a high Physician Assistant National Certifying Examination (PANCE) pass rate, it is only after the completion of significant remediation efforts for an increasing number of students on academic probation. In the past year, the number of students on remediation during the didactic phase has increased by 200%. Most of the students who enter probation and remediate find themselves on remediation again during the first year due to the demands of a rigorous curriculum, often introducing complex subjects and a demanding workload that remediation requirements now compound and create a cumulative impact. A significant challenge to students results from the reality that remediation efforts must be completed with continued coursework. This means that the student on probation is adding to an already intense workload they have already demonstrated a challenge to accomplish successfully.

As program staff and faculty seek to support the students at risk for academic dismissal, PAGI staff are unsure how to approach the current problem. Their efforts are further challenged by the decreased available staff and resources as several faculty and administrative support personnel have left the program and leadership is slow to identify and hire replacements. In the past year, advisors have had a 16:1 student-to-advisor ratio (A. Brown, personal communication, August 18, 2023). The need to balance such high stakes advising tasks with teaching and other responsibilities leads to significant time constraints to focus on the unique needs, challenges, and goals of each student. Admissions personnel serve both as administrators and student success advisors to incoming students. While in optimal positions to capture critical data from applicants and members of incoming cohorts, the accreditation review indicated that staff workloads were unmanageable and in need of improvement.

Addressing this variability first requires understanding the variability and then adapting advice and guidance to individual circumstances, which is time-intensive in the context of already limited resources. The recent impact of such realities is the high faculty turnover.

In 2021, the ARC-PA placed PAGI on probationary status, indicating that the program failed to meet the necessary standards for a PA graduate program. PAGI was cited for lacking evidence of performing critical analysis of available data and ongoing self-assessment. The self-report documentation indicated a lack of understanding regarding data supporting the determination of sufficiency and effectiveness of program faculty and success in meeting the program's goals. The perception is that existing faculty are task-saturated, the program is understaffed, and that data-driven decision-making is severely lacking in supporting student academic achievement and thus, the program's mission.

Background of the Problem

While research is available regarding predictors of academic success for medical school that informs admission policies for screening applicants (Ahmady et al., 2019), with limited research focused specifically on PA graduate education, there is lack of research dedicated to understanding both academic and non-academic predictors focused on the didactic phase of the coursework to support early intervention for students at risk of academic failure. HM students present another layer of complexity. Although studies indicate HM students face unique challenges, it is not well understood how a program can effectively capture feedback for improved understanding of those challenges and their impact on academic performance. At PAGI, faculty and staff face the challenge of effectively identifying students who present the greatest chance at succeeding in the demanding PA program and creating targeted and informed strategies for supporting students throughout the intensive first-year coursework.

In 2020, the COVID-19 pandemic brought about unprecedented challenges for academic institutions, including PA programs, like PAGI. Faculty and students alike struggled to adapt to new learning environments, create meaningful engagements with professors and peers, and meet the rigorous demands of graduate healthcare education (Cetrone, 2023). PAGI identified an increased trend of students failing to achieve satisfactory academic milestones, resulting in a significant increase in first-year students on academic probation requiring remediation. Program leadership concluded that while COVID-19 may have highlighted the trend, the challenges were not a direct result of the COVID-19 unique obstacles but were reflective of systemic challenges within the program.

Program leaders are concerned that their efforts are ineffective in identifying students at risk for struggling academically due to factors that can be captured during the admissions process, but are not (M. Renard, personal communication, August 11, 2023). Although research is available to inform the use of such factors as GPA and previous healthcare experience and their association with academic success in PA programs (Hegmann & Iverson, 2016), PAGI's current program application process is driven by personal preferences, instead of research, and relies heavily on undergraduate transcripts, total hours of relevant work or volunteer experience in a health-care clinical role/setting, and subjective non-standardized interviews (M. Renard, personal communication, August 11, 2023). As the program continues to see a rise in the total number of struggling students within the didactic coursework during the first three terms of the program, there is no meaningful system in place to understand the trends or implement proper interventions to address them. Transcript review combined with comprehensive GPA evaluation in undergraduate academics alone is proving insufficient in identifying students who may need additional resources and/or remediation in critical foundational knowledge in basic human anatomy and physiology as well as biological science concepts.

Following the 2021 accreditation review and in conjunction with the trends regarding incidences of academic probation within the first year of study, the PAGI program staff was interested in understanding how current processes captured necessary insight into factors that impact academic achievement and how predictors were used to design targeted support to decrease the incidence of probation and, potentially, improve the outcomes of remediation (B. Cline, personal communication, April 5, 2023). The goal included identifying a framework for meaningful data collection that facilitated continuous improvement efforts required to meet ARC-PA accreditation standards.

Problem Statement

The primary focus of this research is to understand how PAGI can develop and implement an integrated data strategy to support the early identification of students at risk of academic failure. This issue has been identified through discussions with program leadership, insights from ARC-PA accreditation review results, and data regarding student academic probation. The core problem centers on the need for early detection of students who are struggling academically and ensuring effective communication among key stakeholders to facilitate targeted interventions. The significance of this problem extends beyond the immediate academic context; timely and effective support for students at risk of academic failure is crucial for fostering the development of competent healthcare providers. This is particularly vital as graduates from PAGI often serve historically marginalized communities, where the quality of healthcare has a profound impact. Thus, addressing this issue is not only about enhancing academic outcomes but also about contributing to the broader goal of improving healthcare equity and accessibility.

Relevance and Significance

PA) graduate education programs play a vital role in preparing capable and skilled professionals to meet the dynamic needs of the healthcare industry. Additionally, these programs are the primary supplier of critical healthcare providers from underrepresented populations that support equity of healthcare for patients from similar backgrounds. PAs from HMCs shared cultural understanding allows them to provide culturally competent care, considering the unique cultural, social, and linguistic factors that may influence health beliefs and behaviors (Marcelin et al., 2019). They are more likely to work in underserved communities, contributing to addressing health inequities and ensuring that patients from URM populations receive the healthcare they need (Saha et al., 1999). Finally, PAs from HMCs often have a heightened awareness of the challenges and barriers faced by patients from HMCs in accessing healthcare services and can work to address these barriers (Smedley et al., 2001). Ensuring a consistent pipeline of PA students from HMCs from admission through graduation of accredited PA programs is critical to support efforts advancing healthcare equity and improving the overall well-being of underserved communities.

PAGI Specific Significance

PA students who struggle academically demand more resources to support their progress through the program, their experiences can negatively impact their peers' experiences, and deficiencies within didactic phases may bleed over into clinical performance (Guerrasio, 2016). PAGI is already in a critical state regarding advising and remediation resources. The additional demand of reacting to students who have already surpassed the academic deficiency threshold mandating remediation take place, is an overwhelming load for the program to bear. Identifying a system to reduce the incidence of students requiring remediation decreases the burden on faculty and allows for the reassignment of resources to focus on proactive activities such as teaching, evaluating, and mentoring students.

Literature Review

In the United States, 10–12% of first-year PA graduate students struggle academically, landing in academic probation (Wolf et al., 2020), and approximately 12% of students consider dropping out during their first year (Kilstrom et al., 2022). As attrition negatively impacts the mission of PA programs and wastes critical resources, programs like PAGI focus on trying to identify and admit students who are better prepared to successfully complete their programs as well as ensure adequate support throughout the didactic and clinical coursework.

To improve student retention rates, admissions departments, faculty, and student support stakeholders are challenged with determining best practices in identifying and communicating predictors of academic achievement. The challenge programs face is complex as not all students are alike, and neither are institutions nor their programs. To address these challenges, programs can leverage the findings of studies dedicated to understanding attrition and student support efforts focused on viewing the challenges through the lens of preadmission activities evaluation as well as studies examining effective post-enrollment intervention strategies. In both instances, researchers have sought to determine and effectively identify factors that best predict student success. An initial question then is what are the significant factors that impact student attrition?

Alyahyan and Düştegör (2020) conducted an in-depth literature review on predictors of student success and compiled the following table (Table 1). While the review provided insight into the categorical factors that may impact student academic achievement, the review spanned all higher education and did not consider the interrelatedness of the identified factors.

Factor Category	Factor Description	References	%
Prior Academic Achievement	Pre-university data: high school background (i.e., high school results), pre-admission data (e.g. admission test results) University-data: semester GPA or CGPA, individual course letter marks, and individual assessment grades	(Adekitan & Salau, 2019; Ahmad, Ismail, & Aziz, 2015; Al-barrak & Al-razgan, 2016; Almarabeh, 2017; Anuradha & Velmurugan, 2015; Asif, Merceron, Abbas, & Ghani, 2017; Asif, Merceron, & Pathan, 2015; Garg, 2018; Hamoud, Hashim, & Awadh, 2018; Mesarić & Šebalj, 2016; Mohamed & Waguih, 2017; Mueen, Zafar, & Manzoor, 2016; Oshodi, Aigbavboa, Aluko, Daniel, & Abisuga, 2018; Singh & Kaur, 2016; Sivasakthi, 2017; Yassein, Helali, & Mohomad, 2017)	44%
Student Demographics	Gender, age, race/ethnicity, socioeconomic status (i.e., parents' education and occupation, place of residence / traveled distance, family size, and family income).	(Ahmad et al., 2015; Anuradha & Velmurugan, 2015; Garg, 2018; Hamoud et al., 2018; Mohamed & Waguih, 2017; Mueen et al., 2016; Putpuek, Rojanaprasert, Atchariyachanvanich, & Thamrongthanyawong, 2018; Singh & Kaur, 2016; Sivasakthi, 2017)	25%
Students' Environment	Class type, semester duration, type of program	(Adekitan & Salau, 2019; Ahmad et al., 2015; Hamoud et al., 2018; Mesarić & Šebalj, 2016; Mohamed & Waguih, 2017; Mueen et al., 2016)	17%
Psychological	Student interest, behavior of study, stress, anxiety, time of preoccupation, self-regulation, and motivation.	(Garg, 2018; Hamoud et al., 2018; Mueen et al., 2016; Putpuek et al., 2018)	11%
Student E-learning Activity	Number of logins times, number of tasks, number of tests, assessment activities, number of discussion board entries, number / total time material viewed	(Mueen et al., 2016)	3%

Table 1 Factors contributing to undergraduate and graduate academic success.

An alternative model for understanding predictors of academic achievement is provided by Swail (2004) and the construction of the Geometric Model of Student Persistence and Achievement. This model provides a conceptual model for guiding the following literature review focusing on a multidimensional approach to identifying (a) a student's cognitive and social attributes; and (b) the institutional role in the student experience (Figure 1). The triangular framework supports a diagnostic and supplementary knowledge view of the student.

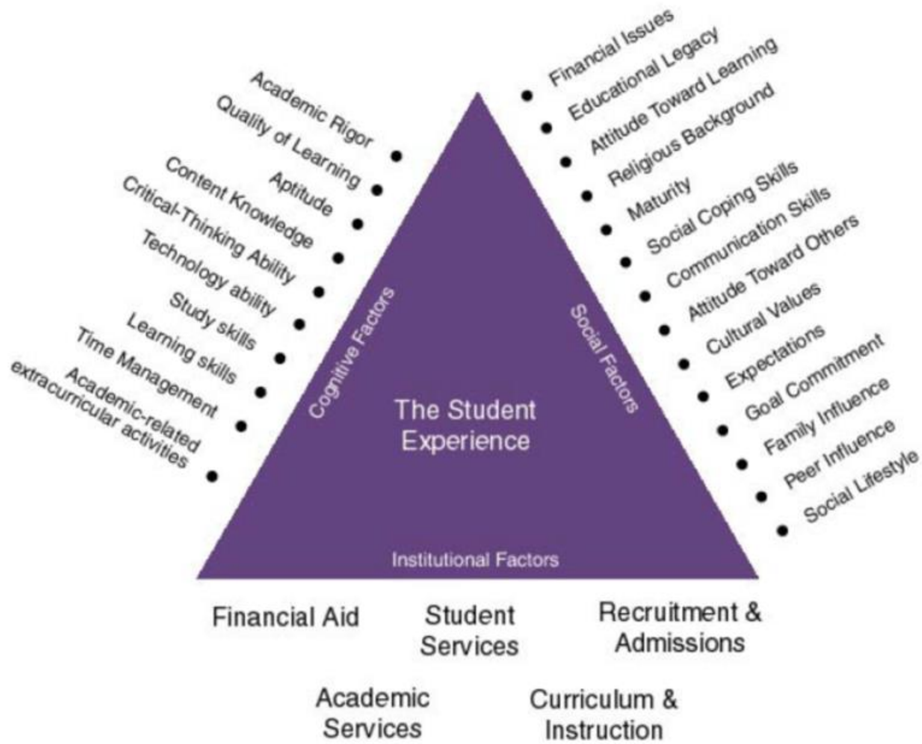

Figure 1 Swail's Geometric Model of Student Persistence and Achievement

Each student is defined by their own cognitive and social factors; some they bring with them to the program and others they demonstrate throughout coursework (Swail, 2004). While the geometric model was established to support the identification of qualified applicants for admission into programs, research dedicated to examining healthcare graduate education indicates that programs require a comprehensive understanding of students that goes beyond the admissions timeframe and persists throughout a student's participation in the program (Bester, 2019; Coplan, 2019; Mann, 2012).

PA programs have increasingly recognized the importance of approaching student success from a holistic perspective that encompasses both academic and non-academic dimensions, acknowledging that the challenges and triumphs of aspiring PAs extend beyond lecture halls and textbooks (PAEA, 2020). The demanding curriculum and high-stakes assessments of the didactic phase can create significant stressors that impact both academic performance and personal well-being (Cetrone, 2023; Kenney-Moore, 2016; McWeeney, 2020; Schempp, 2018). To truly understand the preparedness of a student to succeed and the necessary student support a program should provide, it is imperative to consider individual student experiences, motivations, and well-being in tandem with their academic endeavors.

What Are the Predictors

While Swail's model provides a framework for factors impacting student success, the model is generalized to all students within higher education. To date, there is little formally known about the factors that predict positive or negative academic achievement, specifically during the didactic phase of PA education. Although much has been studied about the predictors of success on the Physician Assistant National Certifying Exam (PANCE) (Moore et al., 2019) and factors associated with successful clinical performance (Opacic, 2001), currently, there are gaps in the research dedicated to understanding predictors of successful student academic achievement during the demanding didactic instruction. To address these gaps and provide a logical model for data collection that will inform student support efforts, this literature review expands the scope to include research focused on all graduate-level healthcare education and what has been written about HM student achievement in higher education. The inclusion of research focused on HM students is based on the mission of PAGI and its intent to educate students from historically marginalized communities who will return to those communities and provide culturally competent care.

Academic Predictors

The didactic phase of PA instruction incorporates an interdisciplinary approach, integrating knowledge from diverse fields of science. This requires students to understand individual subjects and their interconnectedness in meaningful ways. The cognitive factors of content knowledge and aptitude are the primary factors identified in Swail's model addressed in understanding a student's preparedness. Historically, GPA (Kuncel & Hezlett, 2007; Siegert, 2008) and comprehensive examination scores such as the GRE or MCAT are used to predict the success of students in graduate healthcare programs even though research indicates they produced mixed results (Moore et al., 2019). With the understood bias of comprehensive tests toward women and HMCs (Moneta-Koehler et al., 2017) and the unpredictability of such tests across PA education, approximately half of the PA programs, including PAGI, have eliminated the requirement of such tests as part of the program application requirements (Moore et al., 2019). As a result, GPA remains the predominant academic predictor used to determine the likelihood of academic success in the program.

The following predictors were found when looking at what additional academic factors, including academic rigor and academic-related extracurricular activities, impact students' ability to successfully complete the didactic phase. Studies indicate that those students who had experience with rigorous academic environments such as strenuous premedical programs (Strayhorn, 1999), and completed an undergraduate Physiology course were positive predictors of necessary cognitive behaviors for success in graduate medical programs (Davies et al., 2020). Additionally, students who had recent experience with upper-division science courses also demonstrated improved performance during the first year of medical school (Schneid et al., 2022). In understanding the impact of this predictor on HM students, first-generation African American or Hispanic college students from low-income families are more likely to be underprepared because they have not taken higher-level math and science courses prior to entering college (Jury et al., 2015).

PA and healthcare education research focused on understanding the impact of academic-related extracurricular activities relevant to healthcare, specifically previous healthcare experience, has led to mixed results. Previous studies have not found a correlation between previous experience and healthcare student achievement (Brown et al., 2013; Hegmann & Iverson, 2016; Higgins et al., 2010; Jefferys, 2007). However, students who had previous experience perceived their prior exposure as a benefit when facing dynamic and overwhelming healthcare coursework (Davis, 2019). Additionally, faculty perceived students with prior experience as more prepared for healthcare (Jeffreys, 2007). This may suggest that such experience may not have a direct impact on academic achievement, it may impact other factors and the behaviors of students and faculty which impact academic success.

The identification of academic predictors for successful completion of didactic instruction goes beyond pre-matriculation data. Research conducted during the first year of medical school has highlighted that some students are not technically inclined, even if they apply with high GPAs, or they learn differently and struggle with didactic-style instruction (Ratnapalan & Jarvis, 2020). While students may have been able to manage the demands of previous academic coursework, the rigorous demand of 40-hour instructional weeks left little to no time for engaging additional academic support when needed. As a result, their ability to acquire and process new knowledge did not match previously demonstrated behaviors (Ratnapalan & Jarvis, 2020). These students may have demonstrated terrific knowledge and attitudes but when presented with more technical areas many needed extra time or someone to facilitate their learning. This reinforces the idea that a primary objective of student support is monitoring the students' academic performance, throughout the coursework, and identifying the students at risk for inadequate performance (Khan et al., 2019). Without such monitoring, research shows that students are left to self-identify if they are at risk. Many do not recognize they are experiencing hardship until after they fail an exam (Ratnapalan & Jarvis, 2020).

Studies focused on identifying models to monitor and predict student performance have found that academic predictors such as student engagement with online materials within an LMS are useful in predicting student outcomes (Alam et al., 2023). The challenge with identifying student engagement as a predictor is that student engagement is complex and multifaceted. For the purpose of this study, student engagement will refer to behavioral engagement that is identified as observable interactions with faculty, peers, or the instructional material. Research shows that such behavioral engagement predicts academic performance in medical school (Wu et al., 2020).

Non-Academic Predictors

In 2020, the University of California, Davis School of Medicine was ranked the second most diverse medical program in the nation, behind Howard, a historically Black university (McFarling, 2023). It is also ranked among the top 50 medical schools in the country (U.S. News, 2023). The university, however, does not rely on GPA or MCAT scores as a predictor of success or a primary determinant of admissions. Instead, the university focuses on non-academic factors such as grit, resilience, and perseverance to determine the potential of applicants (McFarling, 2023). Their shift in focus from academic to non-academic factors is consistent with the PA research that has shown no relationship between undergraduate GPA, healthcare education GPA, or other academic factors and success in didactic coursework (Brown et al., 2013; Nilson, 2016).

PA programs have evaluated and determined that using such measures as applicants' experience as patient educators, community organizers, or working at community-based organizations are predictors of program success (Coplan & Evans, 2021). These studies demonstrate that while academic performance is essential and knowledge is associated with performance, non-academic factors–certain attributes and personal characteristics–contribute significantly to a student's ability to adapt to the rigorous demands of PA education and complete their degree program and must be considered (Moore et al., 2019).

For proper framing of non-academic factors, the identification includes those predictors of positive academic achievement and those cautionary flags indicating a student may struggle to meet academic standards. A 2020 study focused on the incidence of PA student burnout indicated that 23% of PA students were at risk for depression, and 43% presented symptoms of moderate to severe anxiety, both negatively impacting academic performance (Johnson et al., 2020). Additionally, the PAEA reported that more than 68% of PA students self-reported experiencing emotional exhaustion related to the didactic phase of schooling, 61% experienced feelings of cynicism at least occasionally, life stressors were high to very high for nearly 28%, and school stress was high to very high for almost 65% of students. Depression and stress are identified as predictors of poor academic performance and an increased risk of dropout in healthcare education (Dyrbye et al., 2010).

When looking at the relationship between depression and anxiety and the factors identified in Swail's model, studies have found that students with insufficient coping strategies, an absence of social support, and decreased resilience are at greater risk (Thompson et al., 2016). Medical students are often away from social support such as family and friends when they enter the demanding medical school environment. The increase in stressors and the decrease in support are associated with impaired academic performance and an increase in depression and anxiety (Dyrbye et al., 2005).

Regarding HM students research has demonstrated that students from HMCs experience various personal and contextual factors that significantly shape their academic success or failure. HM students often face unique challenges and systemic barriers such as implicit bias and stereotyping, microaggressions, lack of mentorship, lack of cultural competency[2] among faculty and peers, and financial constraints that affect their experiences and success in graduate physician assistant (PA) programs (Coplan et al., 2021; Chisholm et al., 2021; DiBaise et al., 2015). Such factors can impact students from HMCs at a disproportionate rate compared to their peers.

Aspirational capital, the ability to maintain hopes and dreams for the future, despite obstacles, aligns with many of Swail's social factors and is a predictor of academic success. Students who possess aspirational capital tend to exhibit resilience, determination, and a willingness to overcome challenges (Burgis-Kasthala et al., 2019). Their capacity to envision long-term goals can motivate sustained effort, contributing to a more positive academic trajectory. While a certain degree of pressure can be motivating, an excessive need to prove oneself can be counterproductive. HM students experience

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[2] Cultural competency in the context of faculty instructing students from historically marginalized communities refers to the ability of educators to understand, appreciate, and interact effectively with people from cultures or belief systems different from their own.

overwhelming pressure to excel and communicate the presence of an imposter phenomenon mindset. They may become susceptible to burnout and heightened stress, potentially leading to academic struggles (Bester & Bradley-Guidry, 2022). The presence of strong aspirational capital assists HM students in overcoming challenges and envisioning themselves as successful students, leading to improved academic outcomes (Stanton et al., 2022).

Familial capital is another predictor of academic achievement (Bester & Bradley-Guidry, 2022; Abdulghani, 2014). A robust familial support system can provide emotional sustenance, alleviate stress, and create a conducive environment for learning. When HM students can extend the boundaries of family to include friends, especially in the absence of family in close proximity, they can overcome other stressors and improve their academic outcomes (Stanton et al., 2022).

A well-developed social network that provides access to professional, educational, and emotional support can be instrumental in promoting academic success. Students with strong social connections may benefit from shared study resources, mentorship, and a sense of belonging that positively influences their learning experience. Effective mentorship provides guidance, encouragement, and a supportive environment where students can seek advice and learn from experienced professionals. In predominantly white academic settings, HMs lack racially concordant mentors, both faculty and peers, impacting their ability to experience an inclusive academic atmosphere (Bester & Bradley-Guidry, 2022; Toretsky et al., 2018). Consequently, HMs may experience isolation from peers, faculty, or support systems that can hinder academic success. Students who feel disconnected may struggle to access resources, collaborate, or seek assistance when needed, potentially leading to poor performance.

Finally, when looking at the impact of financial concerns, a 2021 study found that 51% of medical students experienced food insecurity and that such financial stress impacted their academic pursuits (Thorman & Dhillon, 2021). The presence of debt and financial stress impacted medical students' academic performance during the preclinical years (Pisaniello et al., 2019; Vyas et al., 2017).

How to Capture the Predictors

It is not enough to investigate what factors may predict academic achievement; it is necessary to understand what activities may provide evidence of those predictors. Alyahyan and Düştegör (2020) mapped out several different activities and opportunities for data collection (Figure 2).

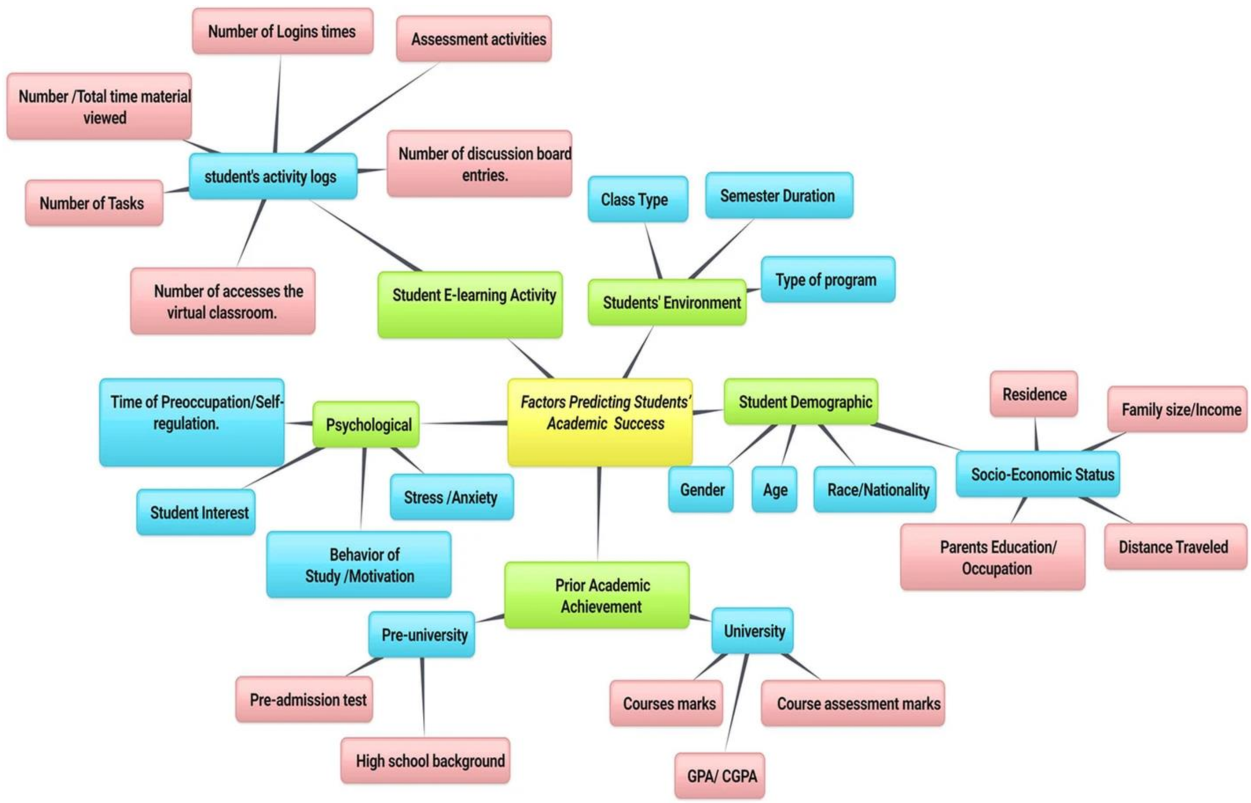


Figure 2 Network map for activities supporting data collection on predictors of academic achievement.

This figure categorizes how previous studies have identified factors associated with predicting student achievement and activities for capturing the data. The findings demonstrate the need for ongoing data capture to understand the pre-existing and emerging nature of different predictors comprehensively.

An ongoing process of identifying predictors is vital due to the dynamic nature of the challenges faced by PA students. For instance, a student with adequate support during the admission process might still struggle with the intensity of the didactic coursework. Alternatively, an HM student may face implicit bias that can impact their academic performance, issues that may not be evident during the admissions process.

Leveraging Technology to Capture Predictors

PA programs such as PAGI have technical infrastructures that may be underutilized in collecting, analyzing, and communicating predictors of students' academic performance. Research focused on predicting students' performance has demonstrated the value of leveraging existing systems and learning applications already employed in many programs for capturing relevant data. While the focus of this study is not on the prediction of performance, such research provides insight into the value of different tools in identifying the existence of predictors for individual students.

Learning Management Systems. Learning management systems (LMS) have a wealth of student data and are increasing their own data analytics capabilities. Such capabilities support educators' understanding of students' engagement with peers, instructors, and course content or activities (Na & Tasir, 2018). The findings indicate that LMS data analytics techniques have successfully identified and predicted students at risk of academic failure, and various types of data were identified as attributes in predicting students at risk of academic failure (Campbell, 2007; Campbell & Oblinger, 2007; Macfadyen & Dawson, 2010).

Student Information Systems. Saa and Shaalan (2020) reviewed existing literature on how student information systems were leveraged to support data mining efforts intended to identify students at risk of academic failure. They found that SIS was leveraged to effectively identify such students and support academic performance prediction by providing student demographics, previous academic performance information, current academic program performance information, as well as other student information. Additional studies confirm the effective use of SIS in capturing predictors and that the use of enrollment data, when paired with additional information regarding student activities, can support early identification and improved student support (Yakubu & Abubakar, 2022). While such studies may have focused on implementing data mining strategies, it is the identification of the SIS as a system that is used to capture predictors that are of importance to this study. Like the institutions involved in the previous research, PAGI utilizes SIS to document student data captured during the application, admissions, and ongoing program coursework activities. The SIS data has effectively supported early identification and, as such, should be considered when thinking about the design of a framework looking to capture a holistic view of a student to support improved academic outcomes.

Existing Early Intervention Frameworks

Purdue University Course Signals

Purdue University's Course Signals was developed as an early warning system developed to identify students at risk of negative academic achievement. The inventors experienced challenges common to many institutions regarding the siloing of student data and the inability to leverage data for a comprehensive evaluation of students to determine whether a student was academically at-risk (Arnold, 2010). The system utilizes demographic characteristics, previous academic history, LMS (Learning Management System) usage data, and performance in the course to date to predict student success. Data from three key systems–Student Information System (SIS), LMS, and a course gradebook–encompassed the Course Signals architecture. While most of the data related to Swail's cognitive factors, as Course Signals focused primarily on student behavior, demographic data indirectly relates to Swail's social factors.

Course Signals is not restricted to identifying students at risk of academic failure but actions the prediction by asking teachers to choose an intervention. Such interventions include personalized email or text message, a notification posted for the student within the LMS, a referral to student support services, or a meeting with the faculty member. While communication is between a computer system and the student–the message is generated by the system–students did not report a negative feeling toward the communication. Instead, they perceived the communication as personal and that it generated a feeling of being seen as more than simply a number (Arnold, 2010). In this way, Purdue's system directly impacts several social factors within Swail's model.

The impact of the system's ability to not only identify students at risk of academic failure but to produce timely communication to spark change in student behaviors was demonstrated by the 21% increase in student retention (Caulfield, 2013). Additionally, faculty perceived the use and impact of the system in a positive light as it helped them understand which students may need additional assistance in a way that was not possible before (Arnold & Pistilli, 2012).

Other Early Warning Systems

Several institutions have investigated the use of early warning systems to support students at risk of academic deficiencies better. Open Universities of Australia proposed the Personalized Adaptive Study Success (PASS) tool to examine socio-demographic characteristics, prior learning experiences, assessments, student engagement with online forums and course content, and others pulled from the LMS, student profiles, and a customer relationship management system. Then, PASS uses a learning analytics engine to analyze the data and then produces reports, feeds, recommendations, and suggestions for learning interventions and strategies (Dipace et al., 2018).

Researchers from Marist College of the Open Academic Analytics Initiative investigated the development of an early detection system of college students at academic risk, using student personal and demographic data, as well as LMS data (Lauría et al., 2013). The OAAI initiative leveraged the research of Purdue's Course Signals project and expanded their interventions to include inviting students to engage in specific remediation activities. Their research found that "low income" students experienced improved outcomes when engaging with targeted communications and remediation activities.

Impact on Accreditation Standards

Implementing a system that supports understanding of students and evaluation of academic achievement demonstrates a program's commitment to effectiveness, continuous improvement, efficient use of available resources, and accountability (Volkwein, 1999). An integrated data system can track academic performance, allowing for early identification of students who are struggling. This enables the program to provide timely interventions and support, which is crucial for student success and retention. Additionally, it streamlines the process of collecting, organizing, and presenting this information, making the accreditation process more efficient and effective.

Universities like Shenandoah University published best practices for supporting ARC-PA requirements. Their comprehensive use of data sources, including end-of-course evaluations, periodic student surveys throughout the lifespan of the program, PANCE data, and advising feedback, supported the demonstration of continuous improvement efforts and targeted revision of program policies and processes (Shenandoah, 2009).

ARC-PA review findings from similar universities to PAGI determined that a well-designed data strategy for program self-assessment and continuous improvement requires collecting both quantitative and qualitative data. It is equally important to demonstrate sufficient data management, analysis, and interpretation (University of Toledo, 2017). Communication was critical in the demonstration of satisfying ARC-PA requirements and active leadership. This indicates the importance of understanding the key stakeholders and their role in the strategy.

Theoretical Framework

No single factor or group of factors has been found to predict didactic performance accurately. Such identification and understanding are complex and critical, serving the needs of both the developing PAs and staff while also fulfilling the requirements of ARC-PA accreditation standards. Evaluation requires and merits adequate time and resources to be effective and efficient. Without additional staff and time, the goal is to identify appropriate mechanisms that support such an evaluation. It is the responsibility of PA programs to develop new methods of assessment that will incorporate the predictive attributes and personal characteristics of PA students.

Technology and data have become integral components of the educational ecosystem, enabling improved capture, dissemination, and analysis of information. Such tools allow improved access to information by staff and faculty and support processes across departments. Despite the increased awareness and usage of such tools, universities continue to struggle to understand how to use them and implementation of these capabilities to support improved student outcomes. This theoretical framework focuses on the utilization of technology and data in the delivery of critical student information to support advising and targeted interventions within a PA program.

To leverage technology, it is necessary to understand how the program's staff and faculty look to understand student behaviors, needs, and unique circumstances that are essential to supporting student success in graduate PA medical education. This includes exploring how the use of current admissions evaluation processes, advising session documentation, and course academic assessment captured within the learning management system (LMS) can gather and communicate predictors of students at risk of academic failure within the didactic periods of instruction.

Through the use of automated proactive strategies, faculty and staff may be able to anticipate student challenges, such as probation, and implement plans to keep these challenges from becoming insurmountable. Monitoring both cognitive—academic performance—and non-cognitive predictors—

self-efficacy, emotional intelligence, and mental health factors—program staff are able to cultivate a more holistic understanding of students, communicate, and target proper interventions to keep HM PA students from falling too far into a hole from which they perceive there is no recovery and dropping-out is the only answer.

Figure 3, below, leverages elements of different early warning systems, such as Purdue signals. From a system model perspective, an activity triggers the use of a system or tool that captures data intended for use by a stakeholder. That stakeholder initiates an action that then impacts a student's behavior in a course. When this is implemented to support reactive actions, communication to stakeholders occurs after the unfavorable behavior occurs and seeks to correct it. In a proactive model, communication takes place to avoid unfavorable behavior.

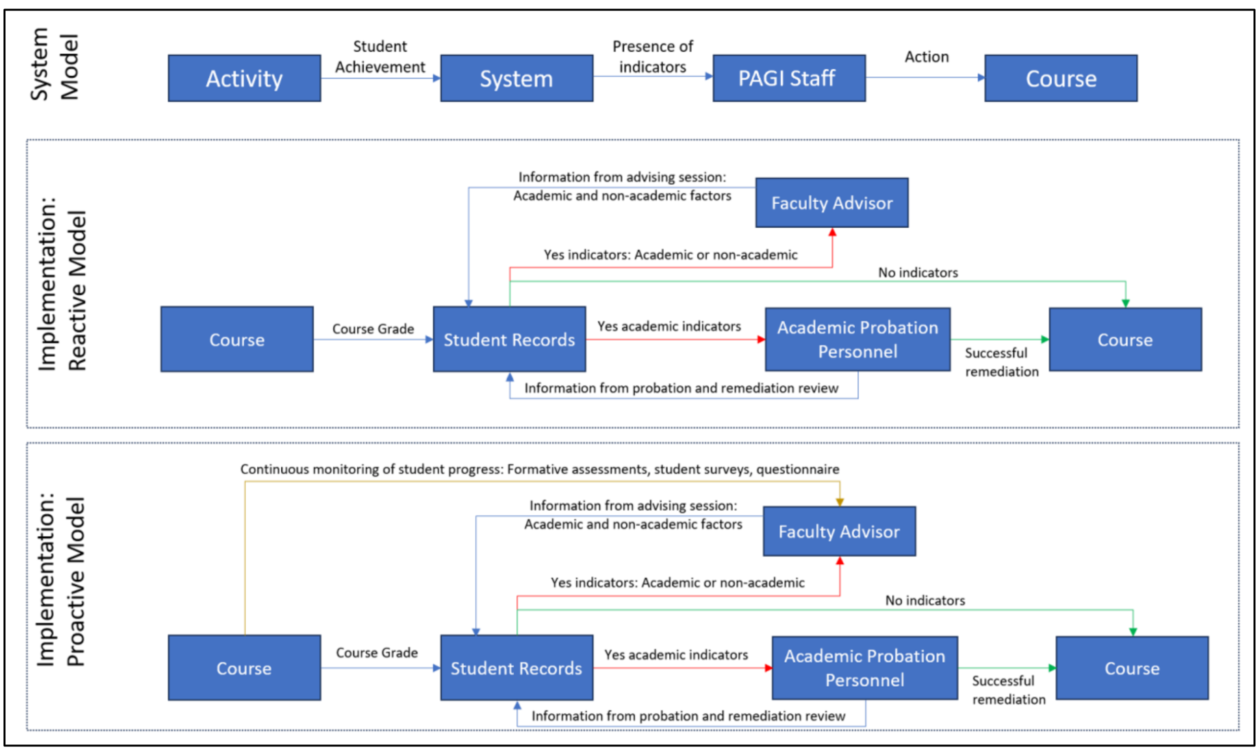


Figure 3 Models for addressing behaviors of students at risk of academic failure.

When seeking to capture a framework that incorporates the preadmissions activities as well as the coursework activities, this study expanded upon the existing frameworks with the following design in Figure 4.

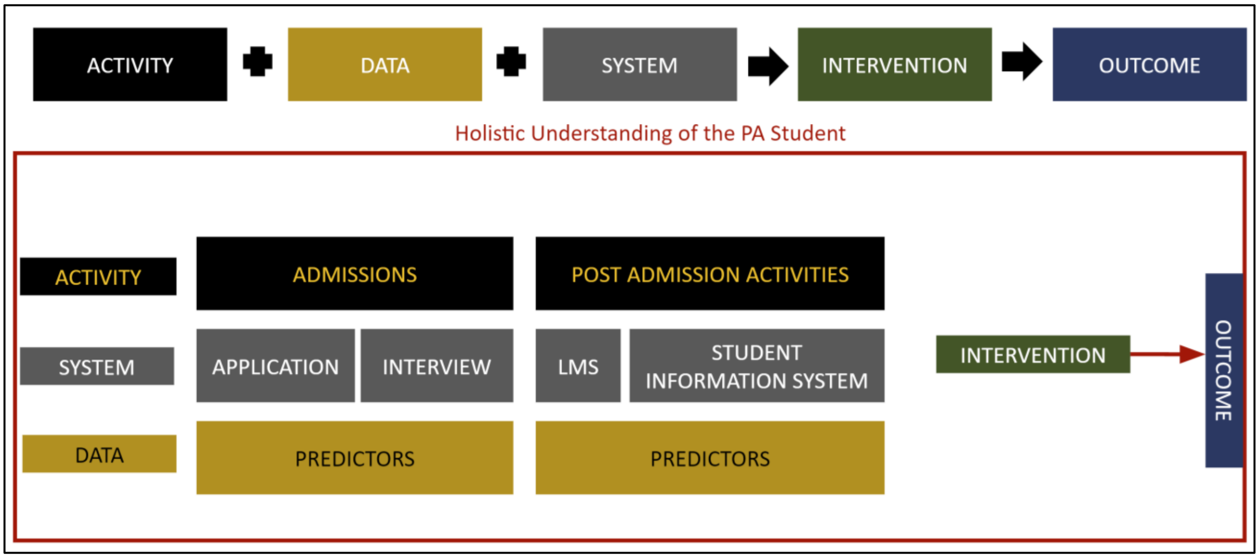


Figure 4 Holistic framework for understanding how PAGI may implement an early warning system to support students at risk for academic failure.

The components of the framework include the activities that take place during the preadmissions and post-admissions processes, the data that is captured during those activities, the systems used to capture and store the data, and the actions that take place because of the data. Understanding these critical components is necessary to inform strategies for data collection to both support students and meet the ARC-PA requirements.

Research Questions

The study's primary aim is to identify the mechanisms for capturing predictors of positive or negative academic performance during both the admissions process and throughout the didactic phase of instruction to facilitate proactive and targeted advising interventions to decrease the incidence of academic probation during the first year of PAGI's program. This aim leads to the following research questions:

- How does PAGI capture predictors of academic achievement to support early identification of students at risk of academic failure?
- What tools capture and inform key student support stakeholders about student experiences, attributes, and metrics that predict negative academic performance?

Methodology

This sequential, explanatory mixed-methods investigation included two parallel data collection paths that we believed would provide evidence to answer our research questions. Program leadership decisions framed our data collection sources and methods based on the limited number of personnel we would have access to and the program documentation we would provide to support our investigation. We intended to interact with multiple stakeholders throughout the program, including students, administrative staff, course faculty, and student advisors. The dean, program director, and academic probation coordinator declined the opportunity to participate in our project for various reasons, and this narrowed our examination of staff communication and information sharing to lower-level administrators and faculty. Additionally, we were unable to gain access to current PAGI students which prevented any examination of the student's experience within both the main program and within the academic remediation program. Without these critical program participants and perspectives, we shifted our data collection to focus on accessible stakeholders, including the lead for didactic academic instruction advising, the lead for curriculum development and associate professor for didactic coursework, and the lead admission and incoming student outreach coordinator. This limited access drove a deeper reliance on document and artifact review and analysis. The triangulation of the qualitative and quantitative data was essential to support our analysis and recommendations adequately. The table below (Table 2) summarizes our research questions and provides a visualization of the data required, combined with our methods of collection:

Table 2 Data collection methods and reasoning

Data Need and Data-Collection Methods for Each Research Objective			
Research Objective	**Data Needs**	**Data-Collection Method**	**Details**
Examine how PAGI understands factors that predict student success.	Documentation of student academic and non-academic factors gathered during the program application phase through first-term didactic instruction	Document review: - CASPA - Admissions scoring rubric - Admissions heat map	What student factors are collected and by whom, and how do these factors align with predictors found in the literature?
Assess standardization of data collection and utilization.	Stakeholder perceptions of data collection requirements, data dissemination, and use cases. Academic probation program policy, criteria, and success metrics	Interviews Document review: -AY probation numbers -Individual course information related to probationary students	Is there a common understanding of the requirements for student data collection from the application period through didactic instruction?
Determine what systems are used to collect data.	Detailed information on the current systems (both interactive digital systems and static file-based systems) used to collect, disseminate and use student data	Interviews System Exploration: - CASPA - SIS - LMS	What systems are available and used to capture student data? Why and how are they used and do they factor into a focus on student success?
Identify how data is communicated throughout multiple stages of the student experience.	Detailed information on communication pathways between different student experience stages (application, admission, and advising throughout didactic instruction)	Interviews	What communication pathways exist to support the visibility of student academic standing between stakeholders? Are those pathways commonly understood? Where are the gaps?

Data Collection

Our first set of data sources included both documentation and artifacts provided by our university point of contact. These resources provide a thorough understanding of how student demographic and academic-related data are currently captured and utilized by both student admissions and course faculty in bringing students into the program and supporting them along their journey.

These sources provide data that supports both of our research questions related to information sharing and ongoing data collection and analysis.

Document Collection.

The first path of our data collection plan focused on existing institutional documentation related to how and to what level the university collects student data to make objective decisions on whom to offer an admission quota and how the program further uses the data to support students socially and academically throughout the program (Merriam, p. 163, 2016). With the support of our program point of contact, we identified and collected documents that captured student academic and non-academic factors within the admissions process and student academic probation program metrics between the academic years of 2018 and 2022. The university made available documents that included student application data, admissions department applicant scoring rubrics, consolidated applicant heat maps, applicant interview protocol forms, and current student academic performance information. The applicant data, scoring rubric and resultant heat map files all provided a granular examination of the type of student data collected, how the data is being used to support individual students, and a means to compare to the list of academic success predictors found in the literature.

ARC-PA Accreditation Report. We requested access to a full review of the program's most recent accreditation review by the ARC-PA. This report was essential to examine an outside stakeholder's view of program leadership, execution success metrics, program staffing requirements and shortfalls, student support services, and any formal course reviews and remediation efforts that may be ongoing throughout our project. This report and the assessments within provide an external baseline view of how the program is performing with respect to data collection and analysis in support of student academic achievement which is essential in addressing each of our research questions. The report also examines and provides an assessment of program leadership and the internal communication between leaders and support staff. This aspect of the report speaks to our second research question related to how the program uses available student data to inform program staff on student academic and human factors related to overall success within the program. Several accreditation standards examine how program leadership conducts program reviews and analyzes the available information to improve curriculum delivery while also improving both student success and satisfaction. There are also standards that address the program's academic remediation policies, program structure, execution, and outcomes. The ARC-PA's assessment of this program informs our faculty interview process while also providing data to support our second research question, again relating to program data collection and analysis in support of improved student outcomes.

Admissions Data. All applicants score sheets and legends explaining the scoring rubric for each weighted informational category were requested to fully comprehend applicants' requirements in each phase of the application process and to examine how the admissions committee is both evaluating and communicating the student data to faculty who are involved in the candidate interview process. In addition, the standard program applicant interview protocol was requested to examine further the breadth and depth of questioning encompassing each interview to again compare these questions and the prospective resultant data to what the literature provides as valid indicators for potential student academic performance. These artifacts of the admissions process provide a comparison view of the information provided by the CASPA[CL1] and the type of additional information program admissions staff require to shape final recommendations on student applicants. It also affords an opportunity to review internal program requirements against the university-level advertised success metrics and whether they were related to student academic success to allow us an opportunity to examine how these relate to perceived student retention priorities.

Probationary Student Academic Data. Student academic performance data within the first program year of didactic, pre-clinical coursework was requested to examine all students enrolled in the Academic Probation program. In collecting these documents, we intended to address each of our research questions by examining whether the admissions data is being used by program faculty to pre-identify students at risk of academic failure and, if so, how the program uses the student data in concert with existing systems to support students throughout their education. The type of data that we requested included entry criteria, performance metrics within, student standing policies while enrolled in the probation program, and exit criteria that inform how students graduate from the probation program. This data is vital to examine any links between the students, their advisors, and the probation program faculty focused on academic success.

Program Goals Artifact. The Program's mission, vision, and goals were obtained through web application searches and publicly available file retrieval. The most recent report on the program's goals and success indicators included student information through calendar year 2022. This source allows for cross-comparison against the student applicant information provided by the admission department to explore commonality or disconnects between what the university deems essential to success and the PA program focuses on when bringing new students into the program. This information provides resources to address our secondary research question on the system tools and data prioritization structure that informs future student support services like academic advising and academic probation staffing.

We drew on the documents above to design preliminary findings that could be tested throughout each interview and through the student support systems exploration. We explain more about this sequential approach in the analysis section below.

Interviews

The second data collection path included virtual Zoom interviews with three individuals closely associated with the applicant review and admissions process, first-year didactic coursework faculty, and student academic advisors to understand the admission process and associated student data more clearly. These individuals were the only program staff we were provided access to and were allowed by program leadership to participate in our investigation. We were also interested in clarifying the extent

to which the admissions department staff communicated with program educators to support the students through the program's first term and ascertain how the admission data may support student-to-advisor pairing. This investigative element is critical to understanding the communication pathways and opportunities that exist between admissions staff and faculty who support both in-class education as well as student advising services. A review of the existing interactions between the departments is essential to examine the tools and systems in place that focus on student academic support and how the data available to both departments is used to inform advisors on academic performance and progress. The individuals chosen for the interview portion of our exploration were identified as critical to the program evaluation by our primary university point of contact. They were selected from the three aspects of student enrollment and education deemed most important to our area of inquiry.
We first standardized a list of questions to focus our conversations on the systems in place that supported student data collection and utilization. The interview protocol was also designed to encourage an open conversation about formal coordination and communication between departments centered on student academic success. These questions directly support both research goals through a subjective discussion centered on the available student academic data and how the data is used in conjunction with all student support activities.

While the documentation review supported the analysis of a structured and historical perspective, we looked towards the interviews to provide context, insight, and depth to complement the provided documentation. Interviews were used to capture the experiences and perceptions of key student support personnel regarding how the organization sought to understand and capture key student success indicators, which the documents and artifacts may or may not overtly reflect.
The interview’s secondary goal was to discuss the current state of student advising, including the overall process, perceived success, limitations, or barriers, and to examine any connections between the advising program and the recent increase in the number of students enrolled in academic probation.

Virtual (Zoom) interviews were conducted and recorded with the following program personnel critical to our understanding of the admissions process requirements, student data strategies, applicant scoring rubrics, didactic instruction, Learning Management System capabilities and utilization, and student advising processes to including intake, scheduling, and academic intervention:

1. Program Admissions Coordinator

   This individual has years of experience with the student application process, candidate heat map, and scoring rubric, including the ties between the CASPA and the program's internal applicant screening process.

2. Program Faculty

   This participant supports the first-term didactic instruction and is intimately familiar with the academic program of instruction, in addition to being a part of the applicant interview panel and a former student advisor.

3. Program Student Advisor

   The student advising representative was chosen due to a wealth of experience within this support activity and the coincidental participation in the applicant interview process and first-term didactic instruction.

Consistent questions were used for all three interviewees to understand historical and any current links between admissions data, the academic probation program, the academic advising process, and the perspective of the recent program accreditation review. An electronic copy of the protocol was provided to each interviewee to fully capture their insights and feedback relevant to the investigation. We received zero responses to our request for written follow-up information using the electronic copy of the protocol. Two recorded interview sessions with three program staff members covered the following areas of responsibility: the primary student application and admissions advisor, a didactic coursework professor and student advisor, a clinical care professor, and a former student advisor. These individuals brought the most experience and insight into the program based on their multiple functions and numerous personal interactions with future and existing students. We inquired about existing connections between the admissions department student and other functions or departments within the program. We wanted to determine if there were any existing pathways of communication between departments that may share student data in support of students, both academically and socially. We also inquired about the origin of the admissions department's policies, procedures, and tools used in reviewing applicants. We needed to gain greater insight into the prioritization of student information and attributes to examine any links to our literature review specific to academic and non-academic predictors of student success. We asked questions that focused on process standardization and student application scoring and how these two facets of onboarding factored into student advising and other student support services within the program. These support our research questions through an understanding of what data is currently collected, how it is collected and shared, and is the data related in any way to what the literature demonstrates as effective predictors of student academic and social success in a post-graduate medical degree program.

Interviews were conducted using MS Teams™ and Zoom™ virtual conferencing applications. The same investigation interview protocol form was used during both interviews.

Support Systems Investigation

We sought access to the student information system and the program's learning management system. We explored the existing capabilities, use cases, faculty perception of value, and feedback mechanisms for students and staff to understand how these systems are currently used and to what end in support of student education. The student information system foundational information was publicly available online, and our program point of contact facilitated trial access from the teacher and manager roles to examine both levels of accessibility, functionality, and interactions between staff and students. The student information system (SIS) pulls student data directly from the CASPA system. It allows additional information to be entered by program admissions staff and course faculty supporting the student advising functions. The SIS is a repository of general student personal information, course transcripts, financial aid information, program and individual course selections, student semester credit loads, and schedules.

Data Analysis

Analysis of Applicant Data. Admissions department student applicant data from the past four academic years consisted of multiple individual academic year MS Excel spreadsheets, which included column headers for each applicant's various weighted personal, demographic, educational, and interview scores. We consolidated all available electronic student applicant data into a singular spreadsheet for cross-comparison of the factors captured for each applicant from year to year. Consolidating the data available for each academic year was required to examine the type and nature of the information used by the admissions department on each applicant, again to provide a crosswalk between the literature and our framework.

The first analysis examined the varying files specific to applicant data. Department personnel color-coded entries using a scoring rubric into a consolidated heat map (Appendix A). Each academic year file differed on the number and specificity of data units collected during the applicant review process. There were a small number of factors that remained constant, and those are summarized in

Table 3:

Table 3: Factors impacting student success as captured by PAGI activities

Academic	● Cumulative Undergrad GPA ● Overall GPA ● Science Pre-requisite GPA
Non-academic	● Home of Record ● Disadvantaged by HRSA ● Self-Identified as Disadvantaged ● Military Veteran ● First-Generation College Student ● Family received public assistance ● English, not the family's native language ● Physical Impairment ● Come from a High School with a low % of graduates. ● Received free-reduced lunches in school

The data found within the applicant spreadsheets was traceable to the Central Application Service for Physician Assistants (CASPA)[CL3], which, as stated earlier, is the centralized application used by most United States physician assistant programs. Our partner organization had chosen to capture and prioritize information from two of the five main sections of the CASPA: 1) Personal Information and 2) Academic History. Applicant biographical information, citizenship, language proficiency, military experience, and environmental and economically disadvantaged information are all categories of information on the applicant heat map and scoring rubric that have roots within the CASPA application system. Academic history is the second of the domains that PAGI focuses on, and it takes the information directly from the CASPA. High school and undergraduate institutional data, professional certifications, and coursework leading to a degree or certification are captured within this domain. This domain also differs significantly between PAGI-collected data and what the CASPA collects. Within the academic history domain, the Graduate Record Examination score is captured by CASPA but not by PAGI, as there is no requirement for a standardized test score during the application process for the

MSPA degree at PAGI. Standardized tests are often linked to aptitude within the literature as they relate to predictors of potential success.

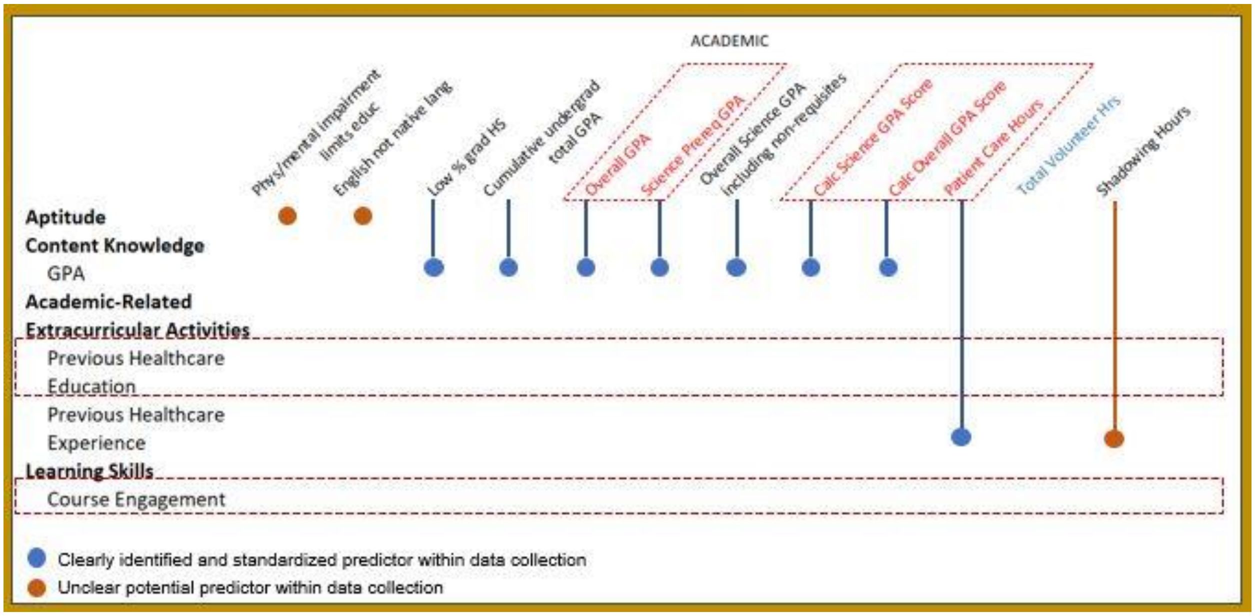
Table 4 below displays the deductive coding scheme used to evaluate the CASPA application. These codes were derived from our theoretical framework and built upon the academic and non-academic factors included in Swail's (2004) Geometric Model of Student Persistence and Achievement described above in the review of the literature.

Table 4 CASPA coding

Academic	Cumulative Undergraduate GPA Overall GPA Core Healthcare Science Course GPA Patient Contact/Care Hours - supervised. Relevant Volunteer Hours StateApply Scores Physician Assistant Shadowing Score
Non-academic Factors	Self-Identified Disadvantaged First Generation College Student Family on Public Subsistence Low Family HS Graduation Rate Free/Reduced School Lunch Program Family Economically Disadvantaged English as a Secondary Language

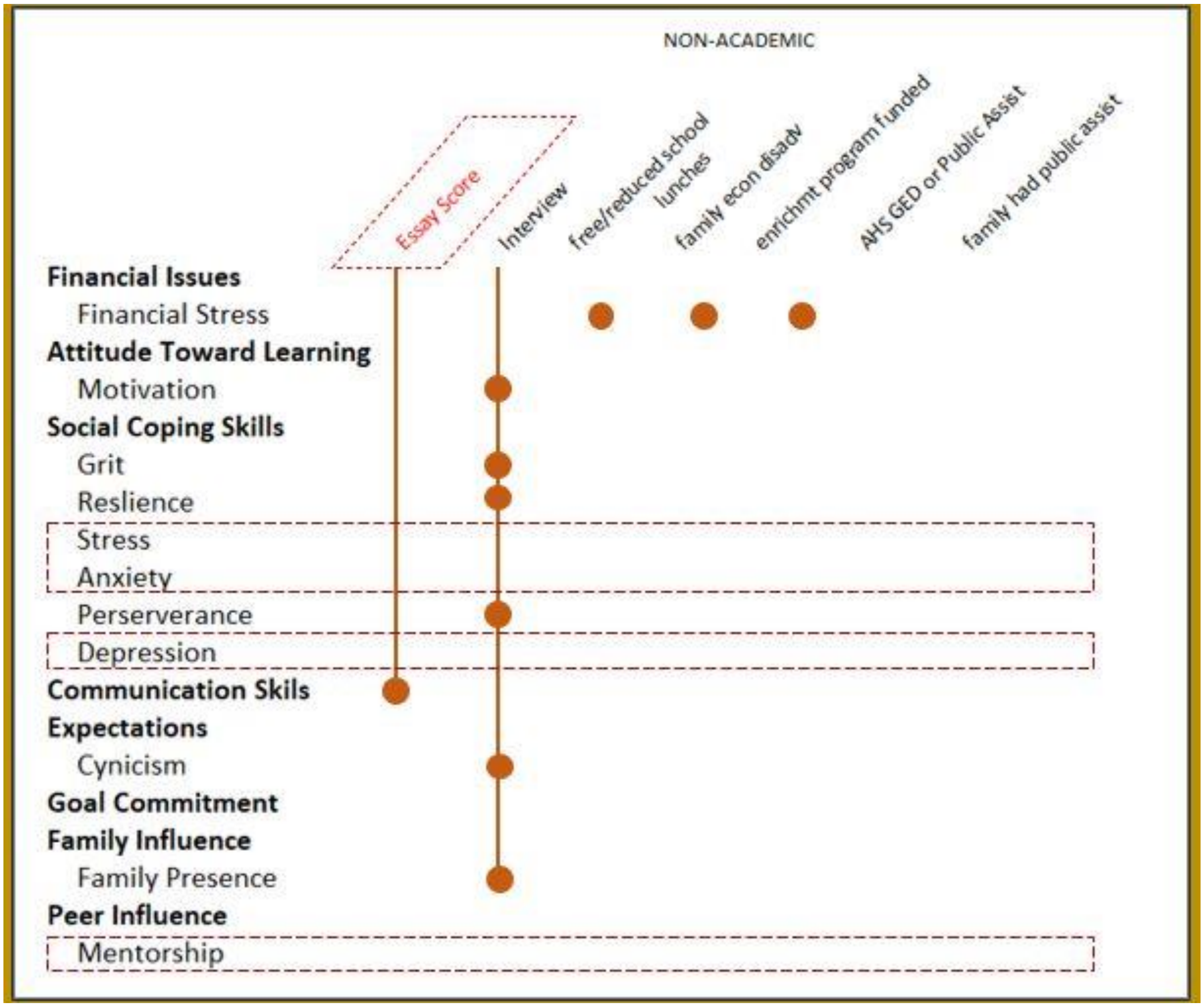
The graphic below provides a crosswalk between the academic predictors of potential student success we found within the literature along the left and the student academic factors collected as part of the application and admissions process. The blue indicators are those that had a clearly defined link to the predictors found in the literature. The brown highlights those indicators that are only subjectively tied to predictors of academic success. The red academic indicators along the top signify those indicators that were consistently captured across all five cohorts that we reviewed. The dashed rectangles are meant to show those predictors found in the literature that have not yet been captured by PAGI during their student application review process.

Figure 1 Academic Factors



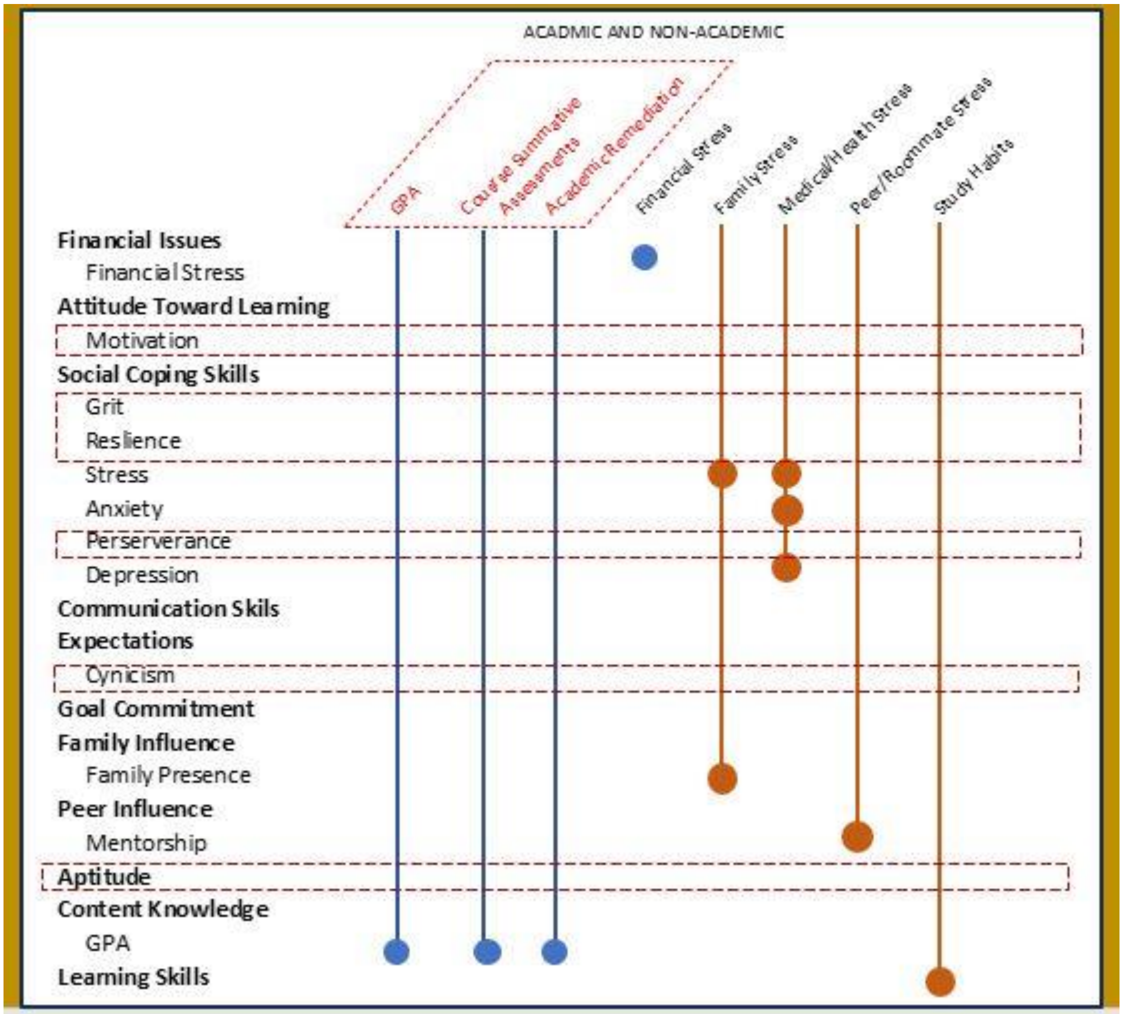
Our second graphic is the crosswalk of the non-academic factors. There were no non-academic predictors captured by PAGI that demonstrated a clear link to the data within the literature. The student essay was the only consistent means of capturing non-academic factors. This graphic shows the increasing gaps between PAGI's required student data and the non-academic predictors of student success. Key indicators that include perceived stress, anxiety, depression, and available mentorship support are not currently a priority within the application review process.

Figure 2 Non-Academic Factors



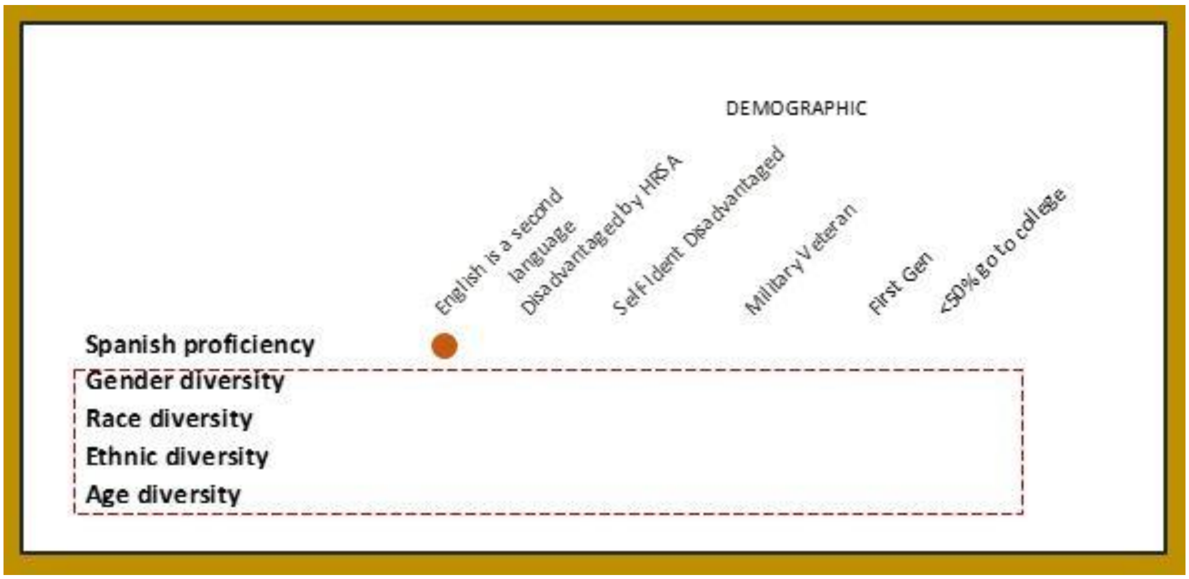
Our third graphic illustrates the predictors captured by the student advisors in support of individual students.   This graphic contains both academic and non-academic factors. Only one predictor (Content Knowledge) is captured by student advisors, and this is measured by previous Grade Point Averages from high school and undergraduate degree programs and current programs' summative assessments. The content knowledge factors were the only factors consistently captured by PAGI for the period under review.

Figure 3 Advising Factors Captured by PAGI Advisors



Our fourth and final student data graphic depicts an internal program misalignment between student demographic information captured during program application and the program's own evaluation metrics. There is no collection of these qualities during the admissions data collection processes. This highlights concerns regarding the overall data collection strategies and alignment with actual data collected during different stages of the program. Additionally, regarding this study's research questions, as students proceed through the program, there is no collection of these qualities as students become at risk for academic failure. Remediation data does not capture whether students on remediation have any of these qualities. Additionally, as the admissions department does not capture this data within its heatmap, there is no streamlined way to determine whether a student will impact, either positively or negatively, PAGI's success metrics. Additionally, there is no way to determine if students with these qualities are at greater risk for academic failure when compared to their peers. The graphic clearly shows the high priority placed on diversity data, but the program does not capture or use this type of data when selecting students for the program.

Figure 4 Program Success Factors vs. Admissions Student Demographics



Analysis of Program Success Metrics. The program publishes, yearly, an MSPA Program Goals and Success Indicators document that highlights the advertised program goals and the metrics that indicate program success. This document advertises two main goals: 1) To produce a graduating class of highly competent physician assistants and 2) To foster a commitment to mission-driven care for diverse and underserved communities. The first goal measures competency through 1) a first-time pass rate for the Physician Assistant National Certifying Examination (PANCE), 2) a summative score on the Objective Structured Clinical Examination (OSCE), and 3) a summative technical skills component. The second goal is measured using three key indicators: 1) graduates who are employed in an underserved healthcare market within one year of graduation, 2) students' ability to speak Spanish at a level of three on the

Interagency Language Roundtable (ILR) scale, and 3) diversity amongst staff and students as measured by gender, race/ethnicity, and age.

Analysis of Accreditation Report. A review of the observations for each program standard contained with the Accreditation Review Commission on Education for the Physician Assistant (ARC-PA) report dated April 2023 focused on a high-level overview of program compliance with supervisory standards and minimal on criteria that focused on individual student success or academic performance. The report observations supported our initial assessment concerning the lack of program data on student academic remediation policies, probation execution, and student remediation outcomes. This is another identified limitation of our project. The report focused heavily on the deficiencies in program leadership, lack of understanding with respect to accreditation standards and policies, and nascent systems in place to evaluate program performance and measure staff manpower requirements, especially within the administrative departments.

Information Technology-based Support Systems

The faculty does not use the SIS for meaningful student support structures or services. The information contained within the SIS is sufficient to support the students administratively but offers very little academic or counseling support. These services must be scheduled external to the SIS and with dedicated support staff.

The learning management system platform provides a vast array of functional capabilities that focus on student communication, student academic performance, resource utilization, and information sharing between faculty and students. Multiple capabilities within the system can track student engagement within each course hosted by the LMS. Several communication and notification capabilities are available that support student engagement, student performance, at-risk indicators, and assignment reminders. The self-paced exploration and interview feedback revealed that the LMS was not fully used by faculty with respect to student tracking capabilities. In most cases, basic content hosting for slides was the only demonstrated use of the LMS in the didactic instruction phase.

Interview Coding

The transcripts for the three interviews were completed using Grain™ transcription software and reviewed and refined by both investigators. We used a straightforward deductive coding approach to explore the interview data, using MAXQDA™ software to better understand our anticipated thematic indicators supporting academic, non-academic, advising, and future efforts to improve the program. Initial coding for the CASPA used two principal codes, academic and non-academic, to create sub-codes for each category to define further what is available to the PA program staff at the time of student application. It was essential to capture sub-codes that would be consistent throughout the coding for the admissions department applicant dataset. We used Deductive Coding through our review of the applicant data to include the CASPA and the admissions data Heat Map consolidated file using a predefined set of codes and subcodes to examine the prevalence of cognitive and social indicators available to the admissions department and ultimately to the individual student advisors. These are essential to answer research questions related to the systems and data available to program staff, the communication flow and timing between the systems, and those that can recognize and utilize the information to benefit each student. (Merriam, p. 197, 2016)

Interview Coding using the completed transcripts again used our project framework to begin the analysis. Then, we expanded the coding themes to include recurring statements and pieces that were common across all three participants. In Table 5, we capture the relevant insights from the two staff interviews to assist us in justifying our findings and recommendations.

Table 5 PAGI staff interview insights - Academic

Code	Subcode	Definition	Purpose/Meaning	Sample
Academic: Comprised of cognitive factors	Content Knowledge	Grade point average, to include core science grades	What data is explicitly captured related to a student's prior content knowledge?	There's a cumulative GPA, and then there's a science-specific GPA. We capture those two numbers.
	Aptitude	The natural or assessed suitability for a specialty degree	The faculty's perception of a student's suitability to be a successful PA is based on prior academic training and related work experience.	A standardized test is not required as part of the admissions process. For example, the GRE or an Emotional Intelligence score.
	External Activities	Volunteer or work-related experience	How the admission department views related experiences in determining potential academic success in the program.	We would talk to the students (during a candidate interview) about their previous PA or clinical experiences.
	Advising	Student Advising	How is the advising relationship established and executed once the student is enrolled?	We now have a standardized intake form we are using during our initial advising interviews.

Table 6 PAGI staff interview insights – Non-Academic

Non-Academic: comprised of social factors	Financial	Means and how the student identifies economically	Are there any barriers to success identified during the admissions process?	We examine this during admissions and the academic review board process to look at human factors contributing to student success.
	Family	Family influence on higher education	What data about a student's familial and cultural background is captured to help inform the advisor/advisee relationship?	Our process does focus on financial, family, and other influencers for student success, especially during the interview portion of the admission process.
	Educational Legacy	Family history related to higher education	How do the immediate family's educational background factor into the admissions process and indicators for student success?	This is part of the intake data from all accepted students to create a sight picture of the potential levels of family support while enrolled in our program.

Table 7 PAGI staff interview insights – Frustrations

Staff Frustrations	Leadership	Direct program leadership	What is the current perception of support given and received from program leadership?	We have a very weak leader, and I think that shows with our faculty attrition.
	Time	Work-related capacity to support students	What is the assessment from current faculty related to the time available to support students across all aspects of the learning experience?	I do not have the time, resources, or expertise to perform all that is asked of me in support of individual students.
	Advising	The faculty's role in student advising	What is the perception of the quality of the advising program, given the limited staff and resources?	We have such a high turnover of staff who serve as advisors that we cannot dedicate the time required due to the volume of students each advisor must support/carry.

Limitations

The program leadership that supported our partnership and project also consciously decided to limit our access to only three individuals who supported the program and its students. This strict limitation inhibited our ability to focus on the individual student's experience. It shifted our focus towards program documentation review, accreditation observations, and student support systems, including advising and top-level information technology-based systems such as the program's student information and learning management systems. We were very fortunate to capture insight and opinions on program performance from the student admissions and application coordinator. This individual left the program shortly after our interview and was no longer reachable for follow-up dialogue in support of our data analysis. The university's main point of contact was instrumental in seeking out and providing access to an individual that has experience with didactic and clinical education, with the applicant interview process as well as served as a student academic advisor.

We lacked the context supporting the construction and content of the student application scoring rubric and whether or how that related to the information captured as part of the CASPA and the state university system standard application. This further limited our ability to assess whether the information was chosen to help identify students at risk of academic failure entering the program. Information on the program's academic probation process and student remediation was limited to only the names and grades of students on academic probation. No information was shared on the remediation criteria or methods and how this information was shared (if at all) with student advisors who were separate and unique from those staff supporting student remediation.

Findings

This investigation explores the current state of the PAGI MPA program and examines program documentation, artifacts, and phenomenological accounts of program operation to answer the project questions. As a reminder, we asked:

1. In what ways does PAGI capture predictors of academic achievement to support the early identification of students at risk of academic failure?
2. What PAGI MSPA processes capture and inform key student support stakeholders about student experiences, student attributes, experiences, and metrics that are predictive of academic performance?

Finding 1 Inconsistent Student Data Collection

PAGI does not consistently capture a full complement of predictors of student academic achievement within their admission processes. The admissions department collected varying categories of student information over a span of five academic years (2021-2025) and consolidated the aggregate data into a Microsoft Excel-based heat map. This heat map is used to score and eventually make admissions decisions on student applicants. (See Appendix A) **The** student admissions informational categories span 24 to 52 academic, socio-economic, and work-experience factors. The Class 2022 admissions data set tracked 26 factors, while the Class 2025 data set amassed 52 columns of student-specific data. The information required of student applicants changed by as much as 66% from one academic year to the next.

The Class 2025 Admissions Heat Map example is provided below:

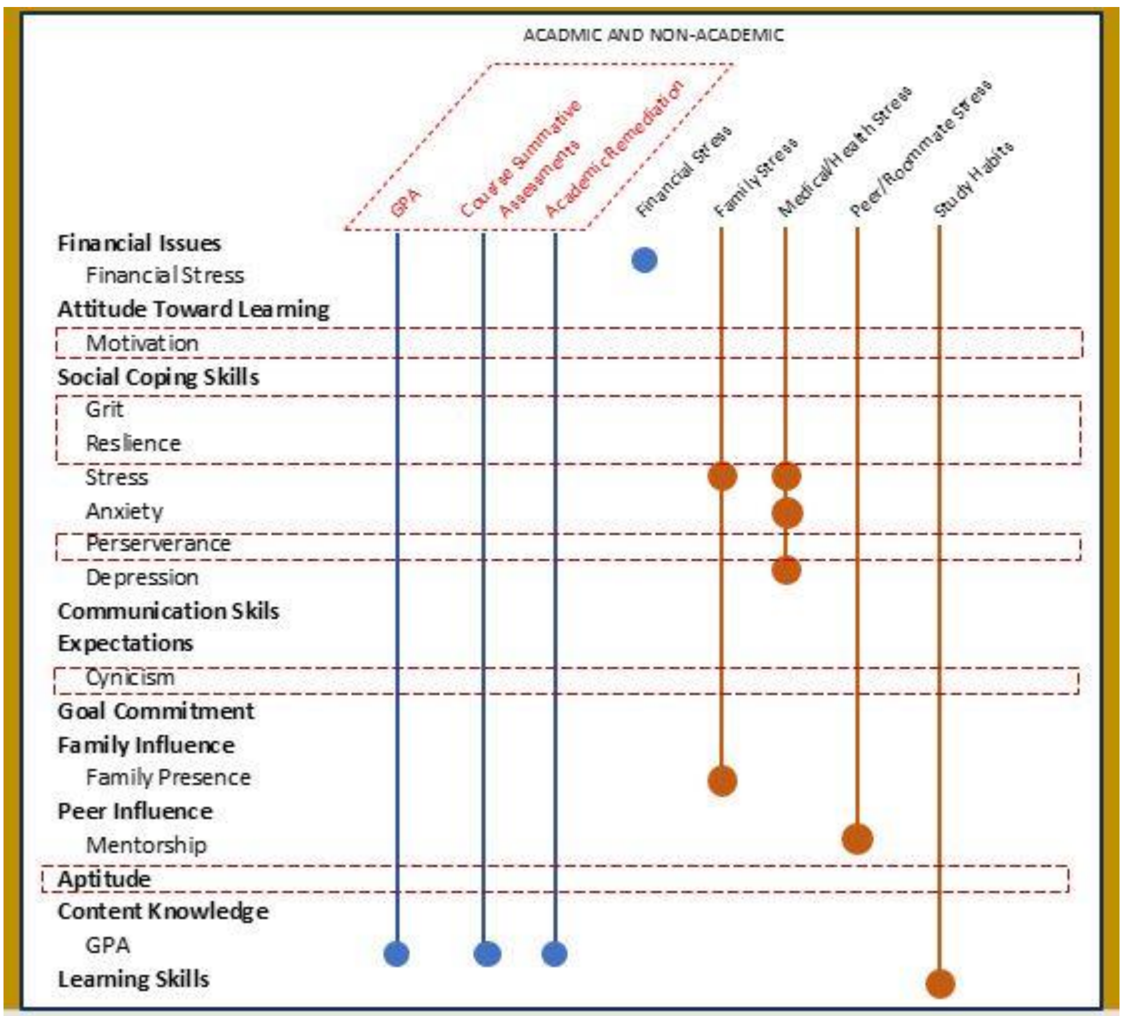
Last Name	First Name	health prof short area	enrichmt program funde	AHS GED or Public	<50% go to college	family econ disadv	English not native	phys/mental impairmen	Number of HRSA Factors	cumulative undergrad total GPA	Overall GPA	Science Prereq GPA	Patient Care Hours	Calc PCE Score	Total Volunteer Hrs	Calc Community Service Score	Calc PA Shadowing Score	LETTERS OF REC SCORE	Essay Score	CASPA Score Sheet Total	FACULTY REC Interview 1to5	GAQ-1	GAQ-2	GAQ Avg	Committee Decision Selected
						Yes			1	3.22	3.22	3.57	4500	2.5	125	0	1	1	1	11	2.5	4.5	3.5	4	Selected
		Yes				Yes			4	3.17	3.17	3.34	1910	0.5	1361	2	1	2	1	12	5	4.5	5	4.75	Selected
							Yes		3	3.96	3.96	3.92	1440	0.5	366	0.3	1	0	1	9.5	5	5	5	5	Selected
							Yes		3	3.28	3.28	3.43	5750	3	1485	2	1	2	1	14.75	4	4	4	4	Selected
						Yes			2	3.18	3.18	3.83	3053	2	792	1	0.5	2	0.5	10.5	2.5	4	3	3.5	Selected
		Yes							2	3.2	3.2	3.6	15688	3	745	0.5	1	1	1	11	4	4	4.5	4.25	Selected
		Yes					Yes		3	3.59	3.59	3.61	3620	2	514	0.5	1	2	0.5	11	2.5	5	4	4.5	Selected
									0	3.12	3.12	3.41	2480	1.5	1060	2	1	1	1	11	4	4.5	5	4.75	Selected
		Yes			Yes				3	3.29	3.29	3.23	4158	2.5	343	0.3	1	2	1	11	4	4	4	4	Selected
									0	3.14	3.14	3.17	16560	5	169	Veteran	0.5	1	1	12.5	5	5	4.5	4.75	Selected
						Yes	Yes		2	3.16	3.16	3.24	4221	2.5	1245	2	1	2	1	12.75	3	3.5	4	3.75	High Alternate
									0	3.51	3.51	3.28	2982	1.5	322	0.3	1	1	1	10	3	4	3.5	3.75	Selected
									1	3.45	3.45	3.51	1560	1	978	1	1	2	0.5	10.75	2	4	4	4	Selected
									0	3.51	3.51	3.04	2910	1.5	2284	3	1	2	1	12	5	3	3	3	Alternate
									0	3.47	3.47	3.51	1571	1	172	0	1	2	1	10.25	2	4	3.5	3.75	Selected
					Yes	Yes	Yes		5	3.4	3.4	3.27	1320	0.5	1000	2	0.5	1	1	10.75	3.5	4.5	4	4.25	Selected
						Yes			3	2.92	3.07	3.91	5305	3	823	1	1	2	1	11.5	3.5	3.5	4.5	4	Selected

The ARC-PA accreditation report (Appendix C), Standard A2.09d, clearly states that the Program Director 'must be knowledgeable about and responsible for continuous program review and analyses. The degree to which the admissions student data set has changed over a short 5-year period points to an inability to conduct reliable trend analysis on how the program's academic and non-academic factors can accurately predict or alert faculty on potential students at risk of academic failure.

Finding 2 Understanding Predictors of Student Academic Success

There is no evidence to support that PAGI has a clear knowledge of valid predictors of student academic performance after examining the program's required applicant data and student information. The academic and non-academic data used by the admissions department to score applicants and offer an admissions quota is not aligned with current literature that outlines defendable predictors of potential academic performance. In conjunction with our first finding, this is significant in addressing our second research question regarding how the program does, or does not, identify key indicators that may predict students at risk of academic failure.

Using this comparative process, we identified a gap between what the associated literature (Swail, 2004) demonstrates as reliable academic success predictors and the student data PAGI MPA program administrators use to assess student applicants with respect to potential academic and clinical success. We refer again to our data analysis graphic that demonstrates the disparity between what is collected by the admission staff and what the literature provides as valid predictors:



We uncovered two salient facts during our first faculty interview related to the origination and utilization of the admissions heat map. The first faculty interview made clear the origination and utilization policy for the scoring rubric and resultant heat map. The second interview revealed that current staff were not involved in the creation or use of the resources critical to bringing new students into the program. Below are excerpts from our interviews that highlight these points:

1. The dialogue below speaks to where the heat map originated from:

   Investigator 1: Can you discuss how the MPA program determines what data to collect and use during the application process and admissions interviews?

   Faculty 2: The program director decided to use this spreadsheet. He referred to it as a 'heat map' and brought it with him from his previous institution. He mandated its use but there was never a discussion about the factors and why they were chosen.

2. This expert from the same interview captures the direction provided by the program director concerning the implementation and maturation of the heat map:

Faculty 2: We were told this is what we would be using for all candidate interviews to score and evaluate each applicant. The program director never solicited input from any current faculty at the onset.

Finding 3 Learning Management System Utilization

Program faculty are not utilizing the full suite of capabilities offered by the program's Learning Management System (LMS) specific to tracking and reporting on student engagement, academic resource utilization and at-risk academic performance during the pre-examination coursework provided during first term didactic instruction. It is evident from our first faculty interview that the LMS is not viewed as a required capability for faculty to use, but more of a convenience if and when they choose to use it to support in-class content delivery. Faculty reported that there is currently no asynchronous content and that all course instruction is done live and in person.

The following excerpt can be found in Appendix B, our first of two faculty interview sessions:

Investigator 2: "Your program offers a Learning Management System, correct? Can you describe how faculty use the LMS during student learning activities?"

Faulty 2: "PowerPoint postings, communication announcements and grades".

The current program LMS provides an extensive list of communication, tracking and reporting functions that are specific to individual courses and also track student engagement across the spectrum of enrolled courses available on the LMS. Faculty input during the focused interview sessions confirmed that only content hosting and file sharing capabilities are being used to support students. It was also clear from our interviews that current and incoming faculty are not provided with any training on the full capabilities offered by the LMS. This is a leading indicator behind why many faculty are only using the bare minimum features to host and share files and to publish announcements or schedule changes.

Our self-paced review of the capabilities offered by the current LMS that focus on student support services, communication and advanced analytics suggested a wealth of untapped resources for faculty to include:

- Attendance alerts – a notice to both students and faculty that a student may be falling behind.
- Assignment reminder alerts – calendar-based alert when assignments are coming due.
- Assignment grade alerts – this alert is for a grade that falls below an acceptable set value.
- Overall grade alerts – alert for an overall GPA within a course that is approaching failure.
- User engagement reports – reports that track course access and module interactions within a course based on number of times accessed and time spent within an activity.
- LMS utilization trackers and reports – higher level report that tracks student log-on information and student resource access displayed in terms of date and duration.

- Observer Role (used to support Academic Advising) – role for advisors and parents that provide insight into how much and to what extent the students are using the LMS for course resources and assignment completion/progression within a course.

The Observer Role function is best situated to support student academic advisors. Advisors who are not primary course instructors/faculty can be enrolled into student courses in a non-credit earning capacity and gain access to all assignments, activities, upcoming events, due dates, and student grades. Advisors can be linked to one or many students simultaneously. Additionally, the LMS offered the ability to create an Advising Hub using the foundational LMS course shell to create a single-source application for all student advisors to communicate outside of student courses and crowd-source advising solutions and best practices. Unfortunately, this capability is not currently being used by faculty or advisors within the PAGI MPA program.

Finding 4 Limited Advising Capacity

PAGI MPA program advising staff are overwhelmed by the current advising load and feel unable to investigate how to adjust advising protocol to increase efficiency and effectiveness. Appendix A provides the yearly total of enrolled students within each 2-year cohort. Appendix B contains the interview data to document the number of current faculty advisors (2) available to students. The ratio of 16 students to 1 student advisor has created a sense of insufficiency and current advisors feel 'overwhelmed' with the daunting workload placed upon them. Below is a brief dialogue from our first faculty interview that included a previous student advisor:

Investigator 1: "What would the advising strategy be to be able to successfully support your students through that first year (of didactic education)?

Faculty 2: I think a low number, like six. Six or seven is ideal. I feel it's very manageable, and I feel like it's not burdensome. If they reach out to me when the number rises to ten or more, it becomes too much. You want them to reach out for help, but then they start kind of reaching *out too much, and then you start getting annoyed. So, I think it's the number of advisees that is the issue.*

The first faculty interview was also very revealing about the lack of collaboration and coordination between the primary academic remediation coordinator and the two available student advisors. Interview participants stated multiple times that there is very little transparency or communication with other faculty regarding how the remediation program is carried out and to what level the students achieve prior to completing the required remediation. The exchange below highlights the perception of the relationship between the academic advisors and the remediation coordinator:

I*nvestigator 1: Do you think that there is power behind data driven decision making within your program?*

Faculty 1: If the data relates in any way to the courses taught by our remediation coordinator, or focused on any of her programs, the data will be overturned or overlooked.

Faculty 2: So that's another thing, related to faculty retention, is that our relationships are not collaborative, they are not inspiring. It's really hard to voice an alternative way to do things (with respect to academic remediation). And I think young faculty with tons of vision and excitement get very frustrated and just give up.

Faculty 1: The remediation program comes up often in our faculty meetings, but the conversation goes nowhere, and this lack of communication makes it very difficult to provide the required support to our students if we do not know how they are doing within the remediation program.

This finding directly relates to both research questions and speaks to the 'how' PAGI can capture meaningful data to anticipate students at risk of academic failure performance while effectively communicating to all stakeholders throughout the program. With only two student advisors, both of which carry a 16:1 ratio of students to advisor, the interview responses were very clear and adamant that the students are not receiving the full benefit of advising services because the time available does not meet the time required to perform this service at an acceptable standard. The stagnant communication between advisors and academic remediation staff also stifles the effectiveness of the advising services. The dramatic rise in probationary students would seem to support this sentiment.

Recommendations

The findings described above present many opportunities for PAGI to engage in change practices that can support the program's ability to address the increased rate of students on academic probation and deficiencies identified in the 2023 accreditation evaluation. The driver diagrams in Appendix E show the identified change practices within a driver diagram to support the reduction of students on academic probation during the didactic phase of instruction.

Driver diagrams offer a visual representation of the relationship between goals, primary drivers, secondary drivers, and change ideas—the recommendations discussed here. This visual clarity helps in effectively communicating complex concepts and strategies, making it easier for PAGI leadership to understand the rationale behind these recommendations. For a quick review, the recommendations are presented as change ideas, or specific actions that directly influence secondary drivers. The secondary drivers are the elements that impact the primary drivers. The primary drivers are elements that must be influenced to achieve the overall aim.

While there are several change practices identified in Appendix E, based on our findings, PAGI is not currently situated to address all of these changes. During the study, the ARC-PA concluded that PAGI was no longer performing at a level necessary for any accreditation status. PAGI had completely lost its accreditation. As a result, we have highlighted the two key practices that PAGI would benefit from as it seeks to rebuild the program and reapply for accreditation in the next 12 months:

1. Articulate and operationalize predictors of students at-risk for poor academic performance; and
2. Staff/System leverage data to determine at risk students.

While these change practices are related to one another, they impact the drivers and aim in distinctly different ways and are related to two independent findings.

Articulate and Operationalize Predictors

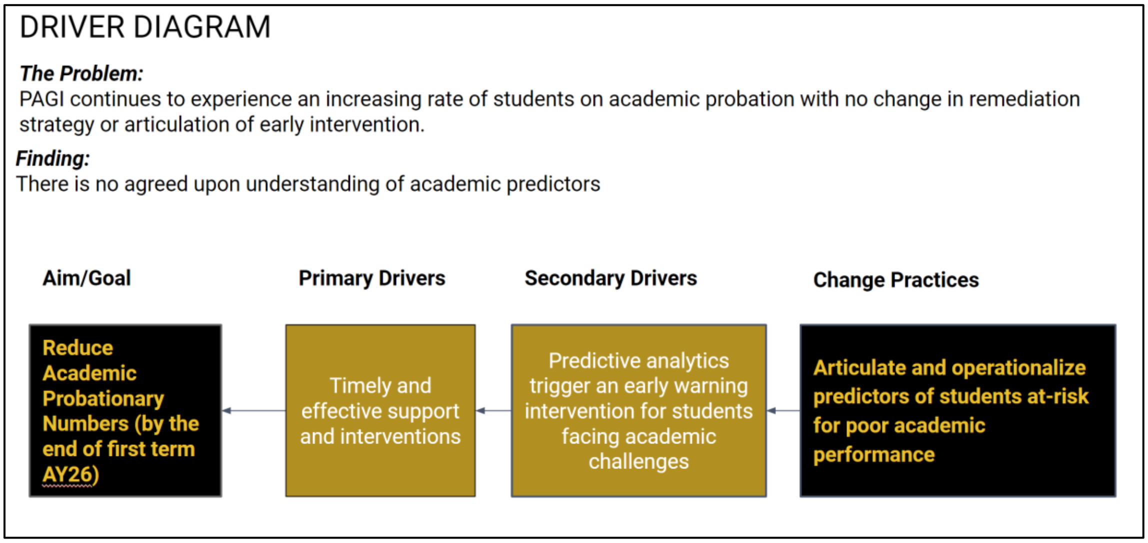


Figure 5 Driver diagram for the recommendation to articulate and operationalize predictors of students at risk for academic failure.

In research question one, we asked how PAGI captures predictors of academic achievement to support early identification of students at risk of academic failure. We found that there was no clear understanding, program identification, or communication among the PAGI staff and faculty regarding predictors of academic achievement. While the PAGI admissions team utilized a standardized heat map to capture information about incoming students, the staff did not know how the tool was aligned to known predictors. Given the observed lack of clarity among program staff and faculty regarding predictors of academic achievement, it is recommended that PAGI define clear, research-backed predictors of academic achievement, operationalizing these predictors so they are measurable and actionable:

- Define clear predictors: Identify and define the factors that are known to predict academic achievement in settings similar to PAGI. Ensure there is scientific evidence to support their relevance to academic achievement. This helps ensure they are not based on personal biases or assumptions.

- Break down broad predictors: If a predictor is broad or encompasses multiple aspects, consider breaking it down into more specific sub-predictors. For example, "student engagement" could be broken down into "frequency of interaction with course materials," "discussion participation," and "quality of contributions." Additional examples exist in Appendix D.
- Operationalize predictors: Translate these predictors into measurable and actionable terms. For example, "student engagement" is a research-backed predictor of academic achievement. PAGI should develop a way to measure student engagement and then use this data to inform early-warning/intervention strategies.

In summary, articulating and operationalizing predictors as a theory of action emphasizes the importance of identifying the key predictors or indicators that are empirically linked to academic failure. The emphasis is on pinpointing those factors that historically and statistically have been shown to correlate with academic struggles. However, beyond mere identification, it's crucial to understand the context and nuances of these predictors. For instance, poor academic performance might be linked to external factors like socio-economic background or internal factors. This understanding is key to articulating predictors accurately. Finally, for each identified predictor, establishing clear, quantitative measurement criteria makes the predictor measurable and trackable. In cases where predictors are not easily quantifiable, such as student engagement or well-being, the development of structured qualitative assessments is required.

This practice allows for a comprehensive review to align predictors of academic achievement with specific intervention strategies. While remediation and intervention were not a direct focus of this research, the end goal is to decrease the rate of students on remediation during the didactic phase of instruction. Research shows that proactive interventions such as proactive advising is correlated with improved PA student performance (Fleming et al., 2022). Alignment was shown to allow the generation of targeted interventions that were directly relevant and addressed the specific challenges students at risk of academic failure faced.

Staff/System Leverage Data to Determine Students At Risk of Academic Failure

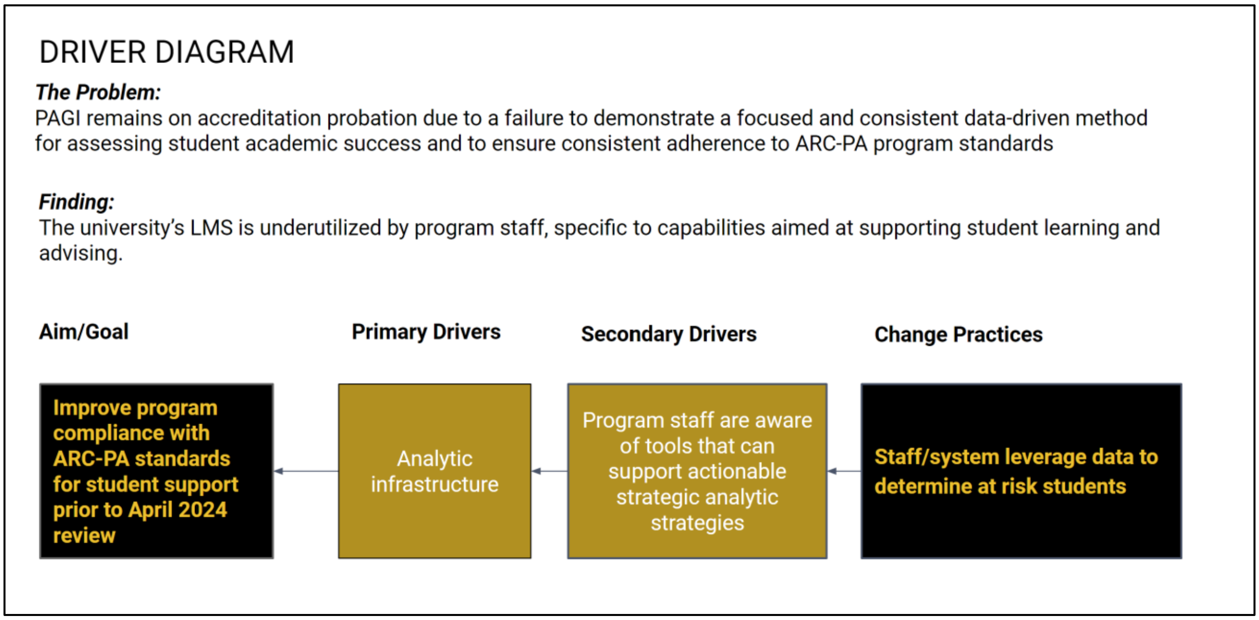


Figure 6 Driver diagram for recommendation: Staff/system leverage data to determine students at risk for academic failure.

With research question two, we asked how PAGI leverages its current systems to support early identification of students at risk of academic failures. Based on the findings of our research, it is evident that there exists a significant gap in PAGI's utilization of its learning management system (LMS) to proactively identify and support students at risk of negative academic achievement. The absence of a coordinated strategy to harness the capabilities of the LMS not only hinders early identification of students at risk of academic failure but also impedes the program's ability to provide timely and effective interventions. Therefore, the following recommendations are proposed. The program should undertake a comprehensive review of how the LMS is situated to identify potential predictors of negative academic achievement within the LMS. Once these capabilities are identified, PAGI should map them to specific data collection and associated intervention strategies. This alignment will ensure that when a predictor is triggered, a corresponding intervention is swiftly and effectively deployed.

PAGI should optimize the use of the LMS to ensure students have real-time access to their academic performance metrics. As indicated in the literature review, academic performance extends beyond formative and summative assessment scores. Research indicates that the LMS can capture critical student engagement behaviors and inform key stakeholders about the potential for negative performance. This will empower students with the knowledge of where they stand academically and what areas might require additional attention. Additionally, a strategically configured LMS can provide students with timely information regarding available academic and social support offerings. This will ensure that students are not only aware of their academic standing but also of the resources available to them. PAGI uses Canvas as the LMS. Canvas has many different analytics options available for programs, staff, and faculty to choose from to provide insight into student behavior and trends. Additionally, Canvas has an active online community with student success stakeholders posting their promising practices such as the early warning strategy available in Appendix D. PAGI can leverage these resources to support their own strategies.

The LMS has regular feedback loop capabilities that can establish effective communications between students and faculty to ensure that the support strategies remain relevant and effective. Feedback should be actively sought from students to understand the effectiveness of the interventions and to identify areas for further improvement.

While these recommendations require initial investment of time from admissions personnel and faculty, and support from the program leadership, they are intended for automated implementation. The current PAGI staff already suffers from workforce gaps in critical areas, requiring staff and faculty to support multiple roles and unable to carry additional administrative burdens. These recommendations would ensure that current efforts are designed for efficiency and effectiveness. They look to leverage the systems that are already in place, requiring no additional cost investment. The benefits of leveraging current system capabilities includes, but is not limited to:

1. Canvas LMS automatically collects vast amounts of data as students interact with course materials. This means faculty don't have to manually gather this information, saving them time.
2. Canvas analytics can provide real-time data on student performance. This allows faculty to quickly identify students who may be struggling and intervene early, rather than waiting for formal assessment periods.
3. Canvas offers predictive analytics, which can forecast students' future performance based on their current engagement and past patterns. This can help faculty preemptively address potential issues.
4. Canvas has standardized reporting tools that present data in easy-to-understand formats, such as graphs, charts, and heat maps. This means stakeholders can quickly grasp trends and patterns without sifting through raw data.
5. Faculty can set up custom alerts for specific metrics. This proactive feature ensures faculty are informed of potential issues without constantly monitoring the system.

With automated analytics and reporting, faculty and advisors are provided critical support when they would otherwise not have the time to spend on such administrative tasks related to tracking and reporting student performance.

Future Research

As this study focused predominantly on staff and faculty perspectives, follow-on research should seek to understand the student perspective, addressing some of the following areas of inquiry.

Student Experience

Gather insights on student experiences, challenges, and perceptions of the support systems in place. This could include understanding their perspectives on the effectiveness of academic advising, the admissions process, and the usefulness of early intervention systems. As the goal of the study was meant to support means of decreasing the incidence of students on probation, follow-on research may seek to focus on student reflections on academic probation. Such research could shed light on the factors that led to their academic challenges and their perceptions of the support received. This could include exploring their views on the probation process, its impact on their academic and emotional well-being, and suggestions for improvement.

Analysis of Non-Academic Challenges

Conducting research to understand the non-academic challenges faced by PA students, such as financial issues, mental health, work-life balance, and family responsibilities, would offer a more holistic view of the factors influencing academic performance. As indicated by the literature review, the non-academic predictors may have the greatest impact of academic performance.

Longitudinal Case Study

As the program is in a redesigned state, it may provide an opportunity for designing a longitudinal case study that follows individual students through their journey in the PA program. Such a study could provide rich, detailed insights into the student experience. This approach would allow for an in-depth understanding of the challenges faced by students at risk of academic failure and the effectiveness of support mechanisms over time. Additionally, comparing student experiences and perceptions across different cohorts could highlight best practices and areas needing improvement. This could involve studying how students from various cohorts perceive the effectiveness of the support systems provided to them.

Conclusion

This research paper embarked on an exploratory journey to understand and address the challenges faced by PAGI in the program's quest to support students at risk of academic failure as well as meet the requirements of the ARC-PA. Through a meticulous investigation that spanned from admissions processes to the experiences of didactic coursework faculty and advisors, we have uncovered pivotal insights into the critical role of data in enhancing student success and program effectiveness.

Key findings from our study support the importance of an integrated data strategy that combines academic and non-academic factors in early identification of at-risk students. This approach requires not just the collection of relevant data but also its strategic analysis and application in real-time decision-making.

The research highlighted that while PAGI captures and possesses student data, the utilization of this data for proactive student support is not fully optimized. It became evident that there is a significant opportunity to leverage existing technical infrastructures, such as the Learning Management System (LMS) and Student Information System (SIS), more effectively. By enhancing these systems' analytical capabilities, PAGI can gain deeper insights into student engagement, performance trends, and potential risk factors.

Furthermore, our study revealed the necessity for improved communication pathways and data sharing protocols among various stakeholders, including faculty, advisors, and program administrators. Establishing a robust data governance framework is crucial to ensure that the collected data is not only accurate and comprehensive but also accessible and interpretable by all relevant parties. This would facilitate more coordinated and targeted interventions to support students.

In conclusion, the research indicates the pivotal role of a well-conceived data strategy and governance in transforming the approach to student support in the PA program. Implementing these recommendations can lead to more informed decision-making, tailored student support services, and ultimately, improved student outcomes. As PAGI moves forward, it is essential to continue refining these strategies, keeping pace with technological advancements, and evolving student and program needs. By doing so, the program can enhance its capacity to nurture successful healthcare professionals, contributing significantly to the broader goal of advancing healthcare education and delivery.

References

Abdulghani, H. M., AlDrees, A., Khalil, M. S., Ahmad, F., Ponnamperuma, G., & Amin, Z. (2014). What factors determine academic achievement in high achieving undergraduate medical students? A qualitative study. *Medical Teacher*, *36*(sup1), S43–S48. https://doi.org/10.3109/0142159x.2014.886011

Ahmady, S., Khajeali, N., Sharifi, F., & Mirmoghtadaei, Z. S. (2019). Factors related to academic failure in preclinical medical education: A systematic review. Journal of Advances in Medical Education & Professionalism, 7(2), 74.

Allam, H., Khan, Z., Letsholo, K., Pandya, B., Shah, K., & Ahamed, J. (2023, May). A Proposed AI Method for Tracking College Students' Academic Progress. In 2023 9th International Conference on Information Technology Trends (ITT) (pp. 215-219). IEEE.

Alyahyan, E., & Düştegör, D. (2020). Predicting academic success in higher education: literature review and best practices. *International Journal of Educational Technology in Higher Education*, *17*(1). https://doi.org/10.1186/s41239-020-0177-7

Arnold, K. E. (2010). Signals: Applying academic Analytics. *Educause Quarterly*, *33*(1). https://eric.ed.gov/?id=EJ890465

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, 267–270. https://doi.org/10.1145/2330601.2330666

Athens, L. (2007). Radical interactionism: going beyond Mead. *Journal for the Theory of Social Behaviour*, *37*(2), 137-165.Bradley-Guidry, C., Burwell, N., Dorough, R. et al. (2022). An assessment of physician assistant student diversity in the United States: a snapshot for the healthcare workforce. BMC Med Educ 22, 680. https://doi.org/10.1186/s12909-022-03717-9

Artiga, S., & Orgera, K. (2016). Key facts on health and health care by race and ethnicity. Kaiser Family Foundation, 7.

Bester, V. S. (2019). African American Physician Assistant Student Success (Order No. 13901694). Available from Ethnic NewsWatch; ProQuest Dissertations & Theses Global. (2288851734).

Bester, V., & Bradley-Guidry, C. (2022). Assessing harmful bias and celebrating strength through the narratives of Black/African American physician assistant students. *The Journal of Physician Assistant Education*, *33*(3), 157–163. https://doi.org/10.1097/jpa.0000000000000435

Blugis, S. (2022, January 26). New data: PA students have diverse backgrounds, life experiences. AAPA's News Central. https://www.aapa.org/news-central/2022/01/new-data-pa-students-have-diverse-backgrounds-life-experiences/

Bradley-Guidry, C., Burwell, N., Dorough, R., Bester, V., Kayingo, G., & Suzuki, S. (2022). An assessment of physician assistant student diversity in the United States: a snapshot for the healthcare workforce. *BMC Medical Education*, *22*(1). https://doi.org/10.1186/s12909-022-03717-9

Brown, G., Imel, B., Nelson, A., Hale, L. S., & Jansen, N. (2013). Correlations between PANCE performance, physician assistant program grade point average, and selection criteria. *The Journal of Physician Assistant Education*, *24*(1), 42–44. https://doi.org/10.1097/01367895-201324010-00006

Burgis-Kasthala, S., Elmitt, N., Smyth, L., & Moore, M. A. (2019). Predicting future performance in medical students. A longitudinal study examining the effects of resilience on low and higher performing students. *Medical Teacher*, *41*(10), 1184–1191. https://doi.org/10.1080/0142159x.2019.1626978

Campbell, J. P. (2007). Utilizing student data within the course management system to determine undergraduate student academic success: An exploratory study. Purdue University.

Campbell, J.P., Oblinger, D.G.: Academic Analytics. pp. 1-20. Educause, Washington, DC (2007)

Caulfield, M. (2013, November 13). *What the course signals "kerfuffle" is about, and what it means to you.* EDUCAUSE Review. https://er.educause.edu/blogs/2013/11/what-the-course-signals-kerfuffle-is-about-and-what-it-means-to-you

Cetrone, K. (2023). Exploring Physician Assistant Students' Perceptions of Stress and Help Seeking Behavior (Doctoral dissertation, Lesley University).

Coplan, B. (2019). How PA Programs Successfully Promote Diversity in Admissions (Order No. 27548607). Available from ProQuest Dissertations & Theses Global. (2348815118). http://proxy.library.vanderbilt.edu/login?url=https://www.proquest.com/dissertations-theses/how-pa-programs-successfully-promote-diversity/docview/2348815118/se-2

Coplan, B., & Evans, B. C. (2021). How organizational culture influences holistic review: a qualitative multiple case study. *Advances in Health Sciences Education*, *26*(5), 1491–1517. https://doi.org/10.1007/s10459-021-10055-w

Davis, L. (2019). Perceptions of Associate Degree Nursing Students regarding the Effects of Previous Work Experiences on Their Academic Success (Order No. 27665259). Available from ProQuest Dissertations & Theses Global. (2331803645). http://proxy.library.vanderbilt.edu/login?url=https://www.proquest.com/dissertations-theses/perceptions-associate-degree-nursing-students/docview/2331803645/se-2

DiMaria, F. (2006, October). Keeping our kids engaged, At-risk kids in college. Education Digest, 72(2), 52-57. Retrieved February 28, 2007, from EBSCOhost database.

Dipace, A., Loperfido, F. F., & Scarinci, A. (2018). From Big Data to Learning Analytics for a personalized learning experience. *Research on Education and Media*, *10*(2), 3–9. https://doi.org/10.1515/rem-2018-0009

Drake, J. K., Jordan, P., & Miller, M. A. (Eds.). (2013). Academic advising approaches: Strategies that teach students to make the most of college. John Wiley & Sons.

Dyrbye, L. N., Thomas, M. R., Power, D. V., Durning, S. J., Moutier, C., Massie, F. S., Harper, W. R., Eacker, A., Szydlo, D., Sloan, J. A., & Shanafelt, T. D. (2010). Burnout and serious thoughts of dropping out of medical school: A Multi-Institutional Study. *Academic Medicine*, *85*(1), 94–102. https://doi.org/10.1097/acm.0b013e3181c46aad

Dyrbye, L. N., Thomas, M. R., & Shanafelt, T. D. (2005). Medical student distress: causes, consequences, and proposed solutions. *Mayo Clinic Proceedings*, *80*(12), 1613–1622. https://doi.org/10.4065/80.12.1613

Francis, B. K., & Babu, S. S. (2019). Predicting academic performance of students using a hybrid data mining approach. *Journal of Medical Systems*, *43*(6). https://doi.org/10.1007/s10916-019-1295-4

Guerrasio, J. (2016). The crucial need for remediation. PAEA News. https://paeaonline.org/resources/public-resources/paea-news/need-for-remediation

Glennen, R.E. (1975). Intrusive college counseling. College Student Journal, 9(1).

Hegmann, T., & Iverson, K. (2016). Does previous healthcare experience increase success in physician assistant training? *JAAPA*, *29*(6), 54–56. https://doi.org/10.1097/01.jaa.0000483097.66394.45

Higgins, R., Moser, S., Dereczyk, A., Canales, R., Stewart, G., Schierholtz, C., Ruback, T. J., McDaniel, J. M., Rhee, J., & Arbuckle, S. (2010). Admission variables as predictors of PANCE scores in physician assistant programs: A comparison study across universities. *The Journal of Physician Assistant Education*, *21*(1), 10–17. https://doi.org/10.1097/01367895-201021010-00002

Honda, T., Sturges, D., Mills, D. C., Yuen, C., Chitwood, R. W., & Rodríguez, J. E. (2022). Predictors of applicant pool diversity among physician assistant education programs: A national cross-sectional cohort study. *Research Square (Research Square)*. https://doi.org/10.21203/rs.3.rs-2288336/v1

Hosch, B. J. (2019). Key Elements of a Data Strategy. In *Data Strategy in Colleges and Universities* (pp. 14-36). Routledge.

Johnson, A. K., Blackstone, S., Skelly, A., & Simmons, W. (2020). The Relationship between depression, anxiety, and burnout among Physician Assistant Students: A Multi-Institutional Study. *Health Professions Education*, *6*(3), 420–427. https://doi.org/10.1016/j.hpe.2020.04.003

Jury, M., Smeding, A., Court, M., & Darnon, C. (2015). When first-generation students succeed at university: On the link between social class, academic performance, and performance-avoidance goals. *Contemporary Educational Psychology*, *41*, 25–36. https://doi.org/10.1016/j.cedpsych.2014.11.001

Kenney-Moore, P. (2016). "Like Drinking Water Out of a Fire Hydrant" Medical Education as Transformation: A Naturalistic Inquiry Into the Physician Assistant Student Experience (Order No. 10075575). Available from ProQuest Dissertations & Theses Global. (1778166723). http://proxy.library.vanderbilt.edu/login?url=https://www.proquest.com/dissertations-theses/like-drinking-water-out-fire-hydrant-medical/docview/1778166723/se-2

Kilstrom, J. L., Neary, S., Roman, C. T., Garrubba, C., LeLacheur, S., & Rhee, J. (2022). Factors influencing physician assistant student attrition rates. *The Journal of Physician Assistant Education*, *33*(4), 341–345. https://doi.org/10.1097/jpa.0000000000000468

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an “early warning system” for educators: A proof of concept. *Computers & Education*, *54*(2), 588–599. https://doi.org/10.1016/j.compedu.2009.09.008

Moneta-Koehler, L., Brown, A. C., Petrie, K. A., Evans, B. J., & Chalkley, R. (2017). The limitations of the GRE in predicting success in biomedical graduate School. *PLOS ONE*, *12*(1), e0166742. https://doi.org/10.1371/journal.pone.0166742

Mann, C. (2012). Faculty Perspectives of the Educational Needs of At-Risk, Underrepresented Minorities in Health Profession Programs (Order No. 3539061). Available from ProQuest Central; ProQuest Dissertations & Theses Global. (1095355648). http://proxy.library.vanderbilt.edu/login?url=https://www.proquest.com/dissertations-theses/faculty-perspectives-educational-needs-at-risk/docview/1095355648/se-2

Marcelin, J. R., Siraj, D. S., Victor, R., Kotadia, S., & Maldonado, Y. A. (2019). The impact of unconscious bias in healthcare: how to recognize and mitigate it. *The Journal of infectious diseases*, *220*(Supplement_2), S62-S73.

McArthur, R. C. (2005). Faculty-Based Advising: An Important Factor in Community College Retention. *Community College Review, 32*(4), 1-I. http://proxy.library.vanderbilt.edu/login?url=https://www.proquest.com/scholarly-journals/faculty-based-advising-important-factor-community/docview/213286778/se-2

McWeeney, M. (2020). Association between Stress and Length of Program in Underrepresented Minority Physician Assistant Students (Order No. 28157953). Available from Ethnic NewsWatch; ProQuest Central; ProQuest Dissertations & Theses Global; Social Science Premium Collection. (2465820197). http://proxy.library.vanderbilt.edu/login?url=https://www.proquest.com/dissertations-theses/association-between-stress-length-program/docview/2465820197/se-2

Mead, G. H. (2018). *George Herbert Mead on social psychology*. University of Chicago Press.

Merriam, S. B., & Tisdell, E. J. (2016). *Qualitative research: a guide to design and implementation / Sharan B. Merriam, Elizabeth J. Tisdell.* (Fourth edition.). Jossey-Bass, a Wiley Brand.

Moore, S., Clark, C., Haught, A., Hinde, B., Reckner, D., Robinson, J., Graham-West, A., Wigal, W., Childers, W., & Horzempa, J. (2019). Factors Associated with Academic Performance in Physician Assistant Graduate Programs and National Certification Examination Scores. A Literature Review. *Health Professions Education*, *5*(2), 103–110. https://doi.org/10.1016/j.hpe.2018.06.003

Na, K. S., & Tasir, Z. (2018). Identifying at-risk students in online learning by analysing learning behaviour: A systematic review. *Proceedings of the 2017 IEEE Conference on Big Data and Analytics*, 118–123. https://doi.org/10.1109/icbdaa.2017.8284117

Nilson, W. A. (2016). Big Five Personality Traits and Other Predictors of Academic Success in Physician Assistant Students.

Opacic, D. A. (2001). The relationship between self-efficacy, outcome expectation, outcome values and physician assistant students' clinical performance: A comparison to the relationship with traditional academic variables (Order No. 3017322). Available from ProQuest Dissertations & Theses Global. (276208710).

Pew Research Center. (2015, September 28). Chapter 2: Immigration's impact on past and future U.S. population change. Immigration's Impact on Past and Future U.S. Population Change. https://tinyurl.com/yc6yz3jy

Pisaniello, M. S., Asahina, A. T., Bacchi, S., Wagner, M., Perry, S. W., Wong, M., & Licinio, J. (2019). Effect of medical student debt on mental health, academic performance and specialty choice: a systematic review. *BMJ Open*, *9*(7), e029980. https://doi.org/10.1136/bmjopen-2019-029980

Ratnapalan, S., & Jarvis, A. (2020). How to Identify Medical Students at Risk of Academic Failure and Help Them Succeed? An Interview with a Medical Educator. *Medical Science Educator*, *30*(2), 989–994. https://doi.org/10.1007/s40670-020-00940-1

Saa, A. A., Al-Emran, M., & Shaalan, K. (2019). Mining student information system records to predict students' academic performance. In *Advances in intelligent systems and computing* (pp. 229–239). https://doi.org/10.1007/978-3-030-14118-9_23

Saha, S., Komaromy, M., Koepsell, T.D., & Bindman, A.B. (1999). Patient-physician racial concordance and the perceived quality and use of health care. Archives of Internal Medicine; 159, pp.997–1004.

Saha, S., Taggart, S. H., Komaromy, M., & Bindman, A. B. (2000). Do Patients Choose Physicians Of Their Own Race? To provide the kind of care consumers want, medical schools might be able to justify using race as an admissions criterion. Health affairs, 19(4), 76-83

Schempp, A. E. (2018). The Making of a Practitioner: Understanding the Lived Experience of Developing Professional Identity in Didactic Physician Assistant Students (Order No. 10784978).

Available from ProQuest Central; ProQuest Dissertations & Theses Global; Social Science Premium Collection. (2030539548).

Smedley, B. D., Stith, A. Y., Colburn, L., & Evans, C. H. (2001). Increasing racial and ethnic diversity among physicians: an intervention to address health disparities. In *The Right Thing to Do, The Smart Thing to Do: Enhancing Diversity in the Health Professions: Summary of the Symposium on Diversity in Health Professions in Honor of Herbert W. Nickens, MD*. National Academies Press (US).

Stanton, J. D., Means, D. R., Babatola, O., Osondu, C., Oni, O., & Mekonnen, B. (2022). Drawing on internal strengths and creating spaces for growth: How Black science majors navigate the racial climate at a predominantly white institution to succeed. *CBE- Life Sciences Education*, *21*(1). https://doi.org/10.1187/cbe.21-02-0049

Thompson, G., McBride, R. B., Hosford, C. C., & Halaas, G. W. (2016). Resilience among medical students: the role of coping style and social support. *Teaching and Learning in Medicine*, *28*(2), 174–182. https://doi.org/10.1080/10401334.2016.1146611

Thorman, A., & Dhillon, H. K. (2021). No Food for Thought: Documenting the Prevalence of Food Insecurity among Medical Students at One Western University. *Journal of Hunger & Environmental Nutrition*, *16*(5), 643–649. https://doi.org/10.1080/19320248.2021.1873885

Toretsky, C., Mutha, S., & Coffman, J. (2018). Breaking barriers for underrepresented minorities in the health professions. Healthforce Center at UCSF.

Vyas, K. S., Stratton, T. D., & Soares, N. (2017). Sources of medical student stress. *Education for Health*, *30*(3), 232. https://doi.org/10.4103/efh.efh_54_16

Wolf, C., Ahmed, A. Z., Schmidt, G., & Winter, S. (2020). Predictors of attrition among accelerated and traditional physician assistant students. *The Journal of Physician Assistant Education*, *31*(4), 204–206. https://doi.org/10.1097/jpa.0000000000000334

Wu, H., Li, S., Zheng, J., & Guo, J. (2020). Medical students' motivation and academic performance: the mediating roles of self-efficacy and learning engagement. *Medical Education Online*, *25*(1). https://doi.org/10.1080/10872981.2020.1742964

Yakubu, M. N., & Abubakar, A. M. (2021). Applying machine learning approach to predict students' performance in higher educational institutions. *Kybernetes*, *51*(2), 916–934.

Appendix A

PAGI MPA Student Application Heat Map (Example)

B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AD	AE	AI	AJ	AK	AM	AN	AO	AP	AQ	AR	AS	AT
Last Name	First Na	Reapplicant	Committee Decision Selected	Alt List Rank	Overall Mission Score	Permanent City	State	Tri-County	Disadvantaged by HRSA Def	Self-Ident Disadvantaged	Military Veteran	First Gen	Low % grad HS	free/reduced school	family had public assis	health prof short area	enrichmt program funde	AHS GED or Public	<50% go to college	family econ disadv	English not native lang	phys/mental impairmen	Number of HRSA Factors	cumulative undergrad total GPA	Overall GPA	Science Prereq GPA	Patient Care Hours	Calc PCE Score	Total Volunteer Hrs	Calc Community Service Score	Calc PA Shadowing Score	LETTERS OF REC SCORE	Essay Score	CASPA Score Sheet Total	Faculty Reviewer	FACULTY REC Interview 1 to5	Interview Invitation (Accept/Decline)	Interview D	Interview Team
			Selected		2	Gonzales	CA	1	Yes	1		Yes		Yes							Yes		3	3.96	3.96	3.92	1440	0.5	366	0.3	1	0	1	9.5		5	Accept	June 22nd PM	
			Selected		3	Brea	CA		Yes	1		Yes		Yes							Yes		3	3.28	3.28	3.43	5750	3	1485	2	1	2	1	14.75		4	Accept	June 22nd AM	
			Selected		1	Manhattan Be	CA		No	0				Yes						Yes			2	3.18	3.18	3.83	3053	2	792	1	0.5	2	0.5	10.5		2.5	Accept	June 22nd AM	
			Selected		0.5	Encino	CA		No	0				Yes		Yes							2	3.2	3.2	3.6	15688	3	745	0.5	1	1	1	11		4	Accept	June 24th PM	
			Selected		0.5	Lincoln	Nebraska		No	0				Yes		Yes					Yes		3	3.59	3.59	3.61	3620	2	514	0.5	1	2	0.5	11		2.5	Accept	June 22nd PM	
			Selected		2	Hayward	CA		No	0													0	3.12	3.12	3.41	2480	1.5	1060	2	1	1	1	11		4	Accept	June 24th PM	
			Selected		0	Pittsburg	CA		No	0				Yes		Yes			Yes				3	3.29	3.29	3.23	4158	2.5	343	0.3	1	2	1	11		4	Accept	June 22nd PM	
			Selected		1.5	San Jose	CA	0.5	Yes	0	eteran												0	3.14	3.14	3.17	16560	5	169	Veteran	0.5	1	1	12.5		5	Accept	June 29th AM	
			4-Offer 11-21-22 dgrimsby@csumb.edu	4	2	Williams	OR	Bay	No	0										Yes	Yes		2	3.16	3.16	3.24	4221	2.5	1245	2	1	2	1	12.75		3	Accept	June 23rd AM	
			Selected		0.5	Hayward	CA		Yes	0.5													0	3.51	3.51	3.28	2982	1.5	322	0.3	1	1	1	10		3	Accept	June 24th AM	
			Selected		1.5	Downey	CA		Yes	0.5				Yes									1	3.45	3.45	3.51	1560	1	978	1	1	2	0.5	10.75		2	Accept	June 29th AM	
			11-Offer 01-05-23	11	3.5	La Canada Fli	CA		Yes	0.5													0	3.51	3.51	3.04	2910	1.5	2284	3	1	2	1	12		5	Accept	June 22nd PM	
			Selected		0.5	Bakersfield	CA		Yes	0.5													0	3.47	3.47	3.51	1571	1	172	0	1	2	1	10.25		2	Accept	June 20th PM	
			Selected		3	Brentwood	CA		Yes	1		Yes		Yes					Yes	Yes	Yes		5	3.4	3.4	3.27	1320	0.5	1000	2	0.5	1	1	10.75		3.5	Accept	June 23rd AM	
			Selected		1.5	Vacaville	CA		Yes	0.5				Yes	Yes					Yes			3	2.92	3.07	3.91	5305	3	823	1	1	2	1	11.5		3.5	Accept	June 23rd PM	

Appendix B

The first interview included both capstone participants as well as a program faculty member and student advisor. The full transcript can be found using the link below: https://docs.google.com/document/d/1bFqMW2bj7DiyXrrLl_xQV3X3yV5nmeXS/edit?usp=drive_link&ouid=109617159695050906080&rtpof=true&sd=true

The second interview included the primary capstone author as well as our primary program point of contact and the lead student admissions advisor. The full transcript can be found using the link below: https://docs.google.com/document/d/1TVEMEmhbBE0to9bK80Rbae_gtv9WgBUm/edit?usp=drive_link&ouid=109617159695050906080&rtpof=true&sd=true

Appendix C

The Accreditation Review Commission on Education for the Physician Assistant (ARC-PA) program review can be found using the link below:
https://docs.google.com/document/d/1VV5C7-aTcFzo4wrqxwABFMnR-WpkLclM/edit?usp=drive_link&ouid=109617159695050906080&rtpof=true&sd=true

Appendix D

Data and Analytics: Early Warning for Students

Posted by Jeff Ferner Mar 6, 2018

One of our goals with Canvas Data was to develop a report that would permit our advising team and administration quick access to see a list of students who are 'at risk' of not passing their course(s). This blog entry shares a report that was created to meet this need. While we started by using Tableau and connected the various tables together within the data source tab, we found that use of a custom SQL query within Tableau to be more efficient.

This report uses the following tables:

- account_dim
- assignment_dim
- course_score_fact
- discussion_topic_dim
- discussion_topic_fact
- discussion_entry_dim *
- discussion_entry_fact
- enrollment_dim
- submission_dim
- submission_fact
- user_dim
- pseudonym_dim

*Note the discussion entry dim was added twice (once for students and once for instructors).

Calculated fields created in Tableau:

Calculation name	Calculation
# Discuss. Posts	COUNTD([id_discussion_entry_dim])
# of Zeros	COUNTD(if [Score] = 0 then [Submission Id] END)
# Submitted & Ungraded	COUNTD(if [workflow_state_submission_dim] = 'submitted' AND ISNULL([graded_at]) THEN [id_submission_dim]
# Unsubmitted & Ungraded	COUNTD(if [workflow_state_submission_dim] = 'unsubmitted' AND [Due] < TODAY() -1 then [id_submission_dim] END)
Unsubmitted 5+?	IF [# Unsubmitted & Ungraded] >= 5 THEN '5+' ELSE "4 or fewer" END
Current Score < 70?	[Current Score] < 70
Score < 70%	IF [Current Score < 70?] = TRUE then "At Risk" ELSEIF ISNULL([Current Score < 70?]) THEN 'No Grades' ELSE "Passing" END
Activity last 8 days?	IF [Last Activity]>= NOW() - 8 THEN 'True' ELSE 'False' END
Career	IF [Crse No.] < '500' then "UG" ELSE "GRAD" END

Important notes:

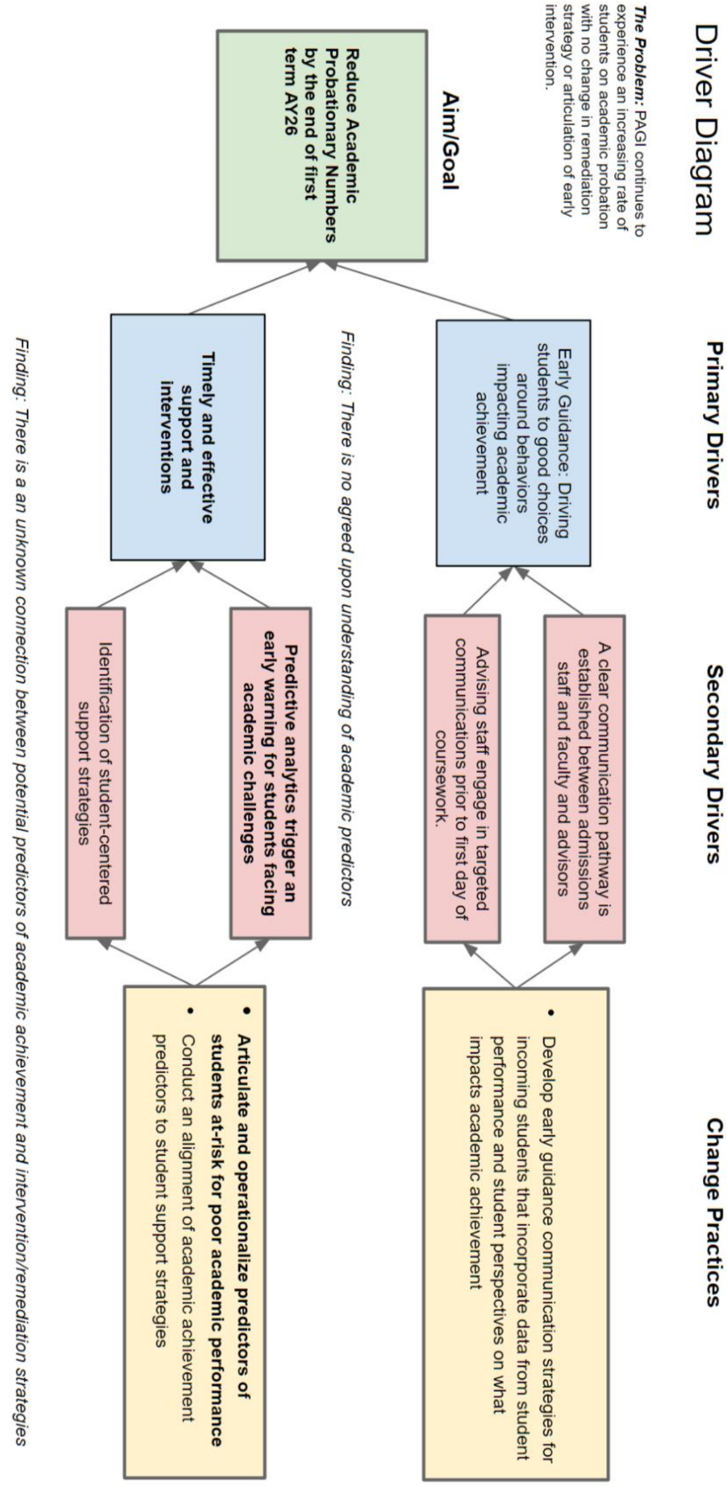
- Our Sis Source Id field is split into six parts in order to create fields for our Term, Course Prefix, Course Number, section, Location code, etc. You will likely need to rework this if you use the attached Tableau workbook as a starting point.
- We have over 130 locations and these are grouped by region or market.
- We use the pseudonym_dim integration ID to add identifying information such as the student home location, Campus name, SIS ID#, etc.
- The report has two sheets with Undergraduate and Graduate students separated.
- Upon opening the .twb file in Tableau, you will be prompted to provide a password to access the data source. Because you don't have access to our data source, you'll need to click on the "Edit Connection" button. Once the connection information is updated to access your Redshift data source you should be able to begin editing the workbook.

URL for original post: https://community.canvaslms.com/t5/Data-and-Analytics-Group/Early-Academic-Warning-Indicator-using-data-from-Canvas-Data/td-p/483761?attachment-id=6721

Additional Canvas analytics resources:

https://computing.sas.upenn.edu/sites/default/files/Canvas%20Data%20Quick%20Start%20Guide%20v1.pdf

Appendix E


Driver Diagram
The Problem: PAGI continues to experience an increasing rate of students on academic probation with no change in remediation strategy or articulation of early intervention.
Aim/Goal
Reduce Academic Probationary Numbers by the end of first term AY26
Primary Drivers
Early Guidance: Driving students to good choices around behaviors impacting academic achievement
Timely and effective support and interventions
Finding: There is no agreed upon understanding of academic predictors
Secondary Drivers
A clear communication pathway is established between admissions staff and faculty and advisors
Advising staff engage in targeted communications prior to first day of coursework.
Predictive analytics trigger an early warning for students facing academic challenges
Identification of student-centered support strategies
Change Practices
Develop early guidance communication strategies for incoming students that incorporate data from student performance and student perspectives on what impacts academic achievement
Articulate and operationalize predictors of students at-risk for poor academic performance
Conduct an alignment of academic achievement predictors to student support strategies
Finding: There is a an unknown connection between potential predictors of academic achievement and intervention/remediation strategies

Driver Diagram