# Quality Enhancement Plan

## EARLY STUDENT SUCCESS SYSTEM IMPLEMENTATION AT JAMES MADISON UNIVERSITY

JMU

JAMES MADISON UNIVERSITY®

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# GLOSSARY/ABBREVIATIONS

AC: Academic Council

AIRR Framework: Anticipation, Inclusion, Responsiveness, Reflexivity

CARS: Center for Assessment & Research Studies

CRM: Customer Relationship Management

ESSS: Early Student Success System

FYRE: First year Research Experience

ISSAQ: Incoming Student Skills & Attitudes Questionnaire

JMU: James Madison University

LMS: Learning Management System

Madison Cares: Alert system within the Dean of Students Offices that handles manual referrals

QEP: Quality Enhancement Plan

QEP LT: Quality Enhancement Plan Leadership Team

QEP WG: Quality Enhancement Plan Working Group

PLT: Provost Leadership Team

President's Cabinet: Advisory group to the president, comprised of divisional vice presidents and selected leadership members from each division

R2: Carnegie Classification for doctoral universities with high research activity

Reengineering Madison: Campus-wide initiative to transform campus technology and platforms over 10 years, modernizing our systems and business processes.

SASEM: Student Academic Success & Enrollment Management

SACSCOC: Southern Association of Colleges and Schools Commission on Colleges

SSLT: Student Success Leadership Team

SALT: Student Affairs Leadership Team

PHOTOGRAPHS BY STEVE ADERTON ('19), NICK LE AND JULIA WEAVER ('21)

# EXECUTIVE SUMMARY

James Madison University (JMU) is embarking on a simple yet aspirational goal with its Quality Enhancement Plan (QEP): to improve student retention and close equity gaps by implementing an Early Student Success System. Student success is more important now than ever as JMU reflects on lessons learned during the first QEP, which focused on ethical reasoning and societal challenges, and as we continue to grapple with the implications of the COVID-19 pandemic, structural inequities, and shifting economic landscapes.

The Early Student Success System (ESSS) QEP builds on JMU's strengths of high-touch support and civic responsibility to meaningfully and directly contribute to three institutional strategic priorities:

1. Being the Change at Work and in the World
2. Advancing Diversity, Equity, and Inclusion (DEI)
3. Attracting the Students of Tomorrow

While JMU's overall retention rate of 89.2% for incoming first-time students might be the envy of many institutions, the last five years have demonstrated that JMU still has work to do. Within the high retention rate, equity gaps exist. For example, first-generation students are retained at 83.1%, Black students at 84.9%, and transfer students at 79.8%. In addition, these rates are trending negatively, with the overall retention rate declining and the equity gaps widening. Finally, students are leaving because as an institution, JMU is not as well positioned to support student success as it needs to be for today's students or for those to come.

The QEP proposes an Early Student Success System that prioritizes a positive, proactive, and asset-based framework that understands student success is not something we do to students, but work toward together. The proposed ESSS combines current and new data insights in combination with the university's new Customer Relationship Management (CRM) platform to identify students not meeting their goals and connect them with people, offices, and resources on campus so that they are better empowered and more likely to reach their goals.

A robust literature review, analysis of institutional data, interviews with peer institutions, and wide-ranging focus groups helped inform our decisions to focus on four primary factors for data collection and student success collaborations to improve student retention:

1. Well-being
2. Basic needs
3. Sense of belonging
4. Academics

A new Early Success & Enrollment Analytics Team will lead, administer, and assess the early student success system, driven by these factors. By better understanding student needs and situations in the moment, the team will leverage the Early Student Success System, in collaboration with colleagues across campus, to work toward closing equity-based retention gaps and improving overall retention by 2% over the next five years.

# A. TOPIC SELECTION

## Background

Established in 1908, James Madison University is a public, national, R2 Carnegie-classified university with a growing, national reputation for offering experiences that lead to an outstanding education and inclusive environment for students, faculty, and staff. The student body includes approximately 20,000 undergraduate and 1,900 graduate students, who are supported by over 1,000 full-time instructional faculty, 400 part-time faculty, and over 1,200 classified staff and administrative faculty.

The institution offers thriving programs in the liberal arts, science and technology, and professional disciplines at the undergraduate, master's, and doctoral levels. JMU is committed to expanding diversity, fostering equity and inclusion, and supporting superlative teaching and scholarship. The institution has achieved national recognition for the high quality of its academic programs, focus on maintaining strong student/faculty interaction, and innovative faculty research. At the heart of these activities, and guiding the institution, is our mission: "We are a community committed to preparing students to be educated and enlightened citizens who lead productive and meaningful lives."

JMU's first Quality Enhancement Plan, The Madison Collaborative: Ethical Reasoning in Action, was selected with wide community feedback and support; carefully developed over two years, and implemented successfully; it provided a strong model for this version. As with the original QEP, JMU's second program proposal integrates broad-based university cooperation but was selected largely based on existing comprehensive planning and evaluation efforts. The resulting project, the Early Student Success System, is a cross-divisional initiative that operationalizes JMU's existing commitment to the university's strategic goals — specifically Priority #2, Advancing Diversity, Equity and Inclusion, and Priority #3, Attracting the Students of Tomorrow — and will enhance students' academic experiences.

## Process

Early in 2019, JMU's senior leadership, in collaboration with the SACSCOC Working Group, began a purposeful review of JMU's existing goals and plans, including the current JMU Strategic Plan, Strategic Priorities, Core Qualities, and University Goals, as well as financial reports, such as the institutional Six Year Plan and projected budgets. Their goal was to identify ideas and areas that were already deemed priorities for the university, as shown by their inclusion in our planning, that could be elevated through the QEP process.

In October of that year, the president and senior leaders identified four key areas for development and consideration:

- Academic Advising and Mentoring
- Racial Equality
- Student Wellbeing
- Retention

It was determined that the next step would be preparation of white papers for each topic to determine if there were ties to JMU planning, explore the potential benefits of the idea by talking with subject matter experts, and provide a solid review of the literature. Based on the selected topics, the appropriate vice presidents selected representatives from their areas with the experience and knowledge to contribute to the research. Early involvement from knowledgeable faculty and staff throughout the process contributed to broad-based support of the university community.

In an example of the cross-divisional involvement that would become a hallmark of the QEP process, the Provost and Vice President for Academic Affairs and the Vice President for Student Affairs each selected someone from their division to serve as QEP Evaluator, a role in which they would work with those writing the white papers to provide feedback and guidance.

Throughout Spring 2020, the two QEP Evaluators collaborated with the SACSCOC Working Group to develop white paper guidelines, which included:

- Summary of Major Issues, including Literature Review
- Possible proposal/s for implementation at JMU
- Brief summary of Learning Improvement Plan for possible proposal/s using LID methodology and links to Student Learning, Student Success, or both
- Essential Budget Items
- Major Works Consulted

PHOTOGRAPHS BY CALEB SCHLABACH AND ELISE TRISSEL

Work began with the distribution of the guidelines during spring semester and extended throughout the summer. During this time, four groups of four to seven faculty and staff conducted research, both externally — to gather best practices and ideas — and internally — with JMU administrators — to ensure there were strong ties between JMU's strategic and budget planning and the topics. In October 2020, the white papers were provided to senior leadership for their review.

The president and vice presidents reviewed the four proposals and discussed the merits and drawbacks of each topic. All papers had elements that were well-liked, would fit the criteria, and would benefit the institution; however, no definitive choice was evident. The group decided instead to combine elements from several of the papers into a new topic.

Retention and student support were identified as the top concepts, but there was significant support for DEI and accessibility as well. Initially, there was a concern that retention and persistence were things JMU currently did well and may not be a significant initiative. However, like all higher education institutions, JMU is already seeing gradual declinings that are likely to increase due to multiple factors. Continued discussions, primarily within Academic Affairs and Student Affairs, further refined the general idea into a topic that combined the best parts of multiple suggestions in ways that were meaningful, measurable, and allow us ensure that future decisions are data driven. In addition, this gave JMU the opportunity to incorporate and leverage important work that was already underway at the university, such as that of the Racial Equity Task Force and the ChangeMaker Task Force.

The resulting topic was an early student alert system, a formal, proactive feedback system that sends notifications about targeted student segments to JMU practitioners who can take action to intervene early in a student's educational career. Writers were chosen to continue developing this idea into a fully formed white paper so that it could be appropriately evaluated in keeping with the assessment of the original four submissions.

This white paper was reviewed by subject matter experts within each division and senior leaders. In March 2021, the Early Alert System was selected as the QEP topic. Please note that during the process, the name of the project evolved to the Early Student Success System.

This QEP topic, primarily a collaboration between Academic Affairs and Student Affairs, called for the design and implementation of a comprehensive early alert system that would reverse the decline in the overall retention rates and narrow the equity gap observed between Underrepresented Minorities; Black, Indigenous, Students of Color; low-income; and first-generation college students at JMU. However, the work was not planned to be done in a silo: Appropriate student support services from across the university would be involved as campus partners identified those programs and offerings most likely to benefit the target audience. The crucial first step in the project was selection of the team that would be responsible for the Early Alert System, which is detailed in section B.

# B. BROAD-BASED SUPPORT

## Support From the Beginning

From the outset, university leadership and the QEP Working Group (QEP WG) sought to build and identify broad-based support for the Early Student Success System (ESSS) QEP. As the selection process demonstrates, the identification of student success, and more specifically closing equity-based retention gaps and raising retention rates, is necessarily a cross division and institution effort. The process to create this ESSS QEP reflects an attempt to build broad-based support in those elements, in part through merging relevant elements of the DEI, advising, early-alert, and well-being issue papers together.

## QEP Leadership

According to Banks and Dohy (2019), equitable student success and retention should be considered the responsibility of every person on-campus, and JMU is no exception. The search for the QEP Director involved:

- Provost and Senior Vice President for Academic Affairs
- Vice President for Student Affairs
- Vice Provost for Student Academic Success and Enrollment Management (SASEM)
- Academic Affairs Chief Communications Officer
- Associate Director for Assessment, Information Technology, and Finance for Student Affairs (AIF SA)

Their involvement on the QEP Director search committee is an example of the support from senior leadership across Academic Affairs and Student Affairs. Moreover, the Vice Provost for SASEM, Associate Director for AIF SA, QEP Director, and Dean of Students went on to form the QEP Leadership Team (QEP LT). The QEP leadership team met almost weekly from June 2021 through the present. Note that the QEP Director is the part-time position hired in May 2021 to serve through the QEP research and design phases, envisioned to end Summer 2023. The QEP Director and QEP WG have requested a budget initiative that includes a permanent full-time director role to lead this initiative.

## QEP Working Group

The QEP Working Group membership also exemplifies the broad-based support for the early student success QEP (see Appendix A). The QEP LT, in consultation with the Provost and Senior Vice President for Academic Affairs and the Vice President for Student Affairs, designed a two-prong process to recruit and select members for the working group.

First, there was an open call to the campus community for nominations and self-nominations to serve on the QEP Working Group. Second, JMU vice presidents were encouraged to nominate someone from their division to make sure it was evident that the widely sourced representation included in the working group had support from senior leadership. The nominees for the QEP WG were then selected and invited to join, ensuring diverse institutional support across divisions, position types, and demographic social identities, with the necessary knowledge and expertise for the QEP content area.

## QEP Campus Engagement

Throughout the research and design phases, the QEP Working Group and QEP Leadership Team worked extensively to build and maintain sustained broad-based support for the QEP as well as larger institutional equity, student success, and retention goals. Regular presentations, updates, and opportunities for feedback were provided for Academic Council, PLT, President's Cabinet, SGA Academic Affairs sub-committee, SALT, SSLT, and the University Board of Visitors (see Appendix B). In addition to these regular updates, the QEP Director and QEP Working Group met with other partners and groups across campus, including the College of Business Center for Student Success, General Education Council, Parent's Council, Advancement Planning & Operations, and more.

Furthermore, the QEP Director and QEP WG sought out insights, feedback, and critical conversations through intentional facilitated conversations. These were important engagement opportunities that functioned as more than just one-way communication about the ESSS QEP; instead, they represented brainstorming sessions, feedback loops, and ways to demonstrate how the QEP was changing as a result of the growing institutional input and support. Some examples of these encounters were the Fall 2021 facilitated student forums, peer-to-peer high impact group conversations, Spring 2022 College of Health and Behavioral Studies Opening Faculty Meeting, Spring 2022 JMU Diversity Conference, ISAT 400 project workshop, Advising & Technology forums, and adviser trainings throughout the Spring 2022, Summer 2022, and Fall 2022 semesters.

## QEP Early Student Success Culture & Infrastructure

The importance of building and sustaining broad-based support for closing equity-based retention gaps and raising overall retention through a program such as an early student success system was recognized early in the QEP identification process. As already mentioned, the collaboration across Academic Affairs and Student Affairs has been consistently integrated through topic selection, the search for a QEP Director, and in the working group. Moreover, as the QEP WG has done the work of researching and designing the necessary structures and cultures required for an ESSS, they have sought to integrate and build shared support for the system. For example, the recommendation for a Retention Committee is consistent with strategic enrollment management (SEM) best practices for breaking down institutional barriers, creating partner and campus community buy-in, and communication (Ruffalo Noel Levitz, 2019). The Retention Committee is made up of partners from across divisions and is charged with growing across-the-board support, distributing data-informed student success and retention insights, identifying student retention best practices oncampus across silos, and facilitating institution-wide communications about the Early Student Success System and equitable student success and retention.

The institution has also committed to building wide support through investment in PROSCI change management certification and training as Reengineering Madison, the QEP, and other major change initiatives occur on campus. Change management supports understanding that support and change don't happen overnight and cannot happen merely by adopting new technologies. Rather, support is built and maintained intentionally over time through motivation, communication, training, interventions, and reinforcement. JMU has identified key members for change management training and certification across areas including Information Technology, Academic Affairs, Student Affairs, and University Advancement. These trained JMU change management practitioners are evidence of the current shared support for the QEP and indicative of the larger support culture being developed.

Numerous key partnerships and collaborations have been developed for the Early Student Success System to be successful. For example, the QEP Director and QEP WG have worked extensively with the Office of Orientation and Transition in the implementation of the Incoming Student Skills & Attitudes Questionnaire (ISSAQ), a survey given to each incoming group of first-year students. The process initially started for the incoming Fall 2020 cohort, but nothing was done with the data. With student success and retention in mind, the QEP Director and WG developed a new pilot for the incoming Fall 2022 cohort, involving the support and insights of Information Technology and University Advising in addition to Orientation and Transition. For the ISSAQ, the QEP WG also collaborated with The Graduate School and three different graduate programs to administer the ISSAQ to graduate students as a pilot to assess whether the ISSAQ will be as useful for graduate students as well as undergraduate and transfer students.

An additional collaboration was created for the QEP between the Office of Institutional Research (OIR) and the Registrar's Office on issues related to data access, privacy, querying, reports, and benchmarking. OIR was instrumental in developing data dashboards for retention that the working group has used for research and to understand student retention at JMU. The Registrar's Office and Information Technology assisted in developing various reports that were used on an ad-hoc basis, including rosters of incoming students for ISSAQ administration, and key components of the Early Student Success System, such as reports of students who have dropped from full-time student status (12+ credit hours per semester) to less than full-time student status (< 11 credit hours per semester).

In similar partnerships, the QEP Director and working group have collaborated with the Center for Faculty Innovation on faculty needs, expectations, and opportunities for early student success engagement; JMU Libraries to explore how Canvas, the university's LMS, may yield actionable insights for student success and retention and to understand best practices for data equity, privacy, and ethics; and Student Athletics for learning best practices from their student success and retention efforts, how the Early Student Success System can support student-athletes, and even different ways of defining retention based on NCAA recommendations.

## Student Participation in the QEP

The QEP director, leadership team, and working group have intentionally and actively sought student involvement in the process of researching and designing an early student success system. Student participation was considered critical for this QEP, especially since the goals included to better understand why students leave JMU, how students are successful, and what concerns students might have about data sharing, privacy, and other issues. More than just participating in some focus groups and giving feedback, the director and leadership team believed having meaningful student involvement throughout the process was crucial. The QEP Director worked with members of the leadership team and campus community early in the process to identify students who would be willing to be a part of the working group and be compensated for their time.

During Fall 2021, four undergraduate students committed to serving on the working group, and two of them served in different capacities for a short period of time. By the end of the semester, none of the undergraduate students remained on the working group due to other on-campus commitments, including their course work. After attempting to recruit more students into the working group, the group decided that inviting students to serve on the working group, even in paid positions, was not ideal because of time commitment, scale of conversations, and lack of general interest. Instead, the QEP Director and QEP WG chose to work with First Year Research Experience (FYRE) to identify and recruit undergraduate students for paid opportunities working with the QEP Director on research related to understanding student retention at JMU, equity gaps, and design of the ESSS. In Fall 2022, two undergraduate students participated in the QEP FYRE research opportunity. For Spring 2023, the two undergraduate students are continuing, and three new undergraduate students have joined the undergraduate research team.

During the Summer 2021 term, the QEP Director met with the Executive Director of JMU's Center for Assessment and Research Studies (CARS) to discuss having a graduate student devote some or all of their time to supporting the QEP. After meeting with a potential doctoral student, all agreed that it was a good fit in terms of need, interest, and expertise for the doctoral student to spend half of their graduate assistantship as part of the QEP WG and providing data analysis support. The doctoral student worked in this capacity throughout the 2021-22 academic year. At the end of the year, all agreed that the relationships and work were mutually beneficial and further need existed. The doctoral student continued working in this capacity into the 2022-23 academic year on a full-time basis, with all of their assistantship hours supporting the QEP through participation in the working group and data analysis. A second graduate assistant was added to the QEP WG and will provide data analysis and project support for the QEP and the Office of the Registrar. This student is supporting the QEP for half of their assistantship assignment during the 2022-23 academic year.

In addition to the sustained undergraduate and graduate student participation in the QEP through research and working group service, the QEP Director and working group sought out student feedback in various channels. For example, toward the end of Fall 2021, and prior to the IRB-approved focus groups, the QEP Director facilitated multiple informal discussions with students about student success, equity, and the use of data. Feedback from these sessions helped inform the design and implementation of the QEP focus groups held for students during Spring 2022. The QEP Working Group also presented updates and solicited feedback via a presentation at the JMU Diversity Conference, with students included in both the presentation and in the audience. Moreover, the QEP Director regularly provided updates to and received feedback from the Student Government Association via the complete governing body and their Academic Affairs subcommittee. A member of the working group also selected ESSS and data ethics as a case study for their class, providing another opportunity for students to workshop ideas, share concerns, and provide feedback directly to the working group member and QEP Director.

# C. STUDENT SUCCESS

Increasing the number and diversity of students who have access to and benefit from postsecondary education is at the heart of the student success agenda (Kinzie and Kuh, 2017). Student success requires defining and illustrating how institutions commit to ensuring that students stay and succeed. The student success goal of the ESSS QEP is to close equity-based gaps in retention rates and increase overall retention rates at JMU through a data-informed early student success system. This section provides an overview of the proposal, the framework for moving forward, and the process used to arrive at these recommendations.

## Overview

The proposed Early Student Success System is designed to leverage data and technology to provide early insights and indicators that can connect students with resources, people, and offices on campus prior to students not meeting their goal. Early refers to early insights, not waiting until an end-of -semester grade or withdrawal from the university, rather than early students, e.g., a student in their first or second year at JMU. The ESSS QEP proposes the implementation of five components to build the infrastructure and personnel necessary to move toward a more equitable culture of student success and retention at JMU. The five components are Early Student Success System, Early Success and Enrollment Analytics Team, Advisers, Retention Committee and Data Committee.

## Infrastructure

The framework guiding the selection, design, and implementation of these five components represents a shift from a deficit mindset to a student empowerment and success framework, viewing students as active agents and asset-based. This is most evident in the change in the language used to title this initiative. Its original proposal described the initiative as an "early alert system," which evolved to an "early student success system." With this shift in mind, the working group based its decisions on foundations, frameworks, and values that:

- Are evidence-informed (using research, data, stories to inform our design and implementation)
- Use an empowerment framework (empowering students as active agents; asset-based)
- Require instilling Culture Change (technologies are necessary, but not sufficient; is institution ready for students?)
- Follow an AIRR framework for responsible innovation (Anticipation, Inclusion, Reflexivity, Responsiveness)

The data included in the first phase of the Early Student Success System includes:

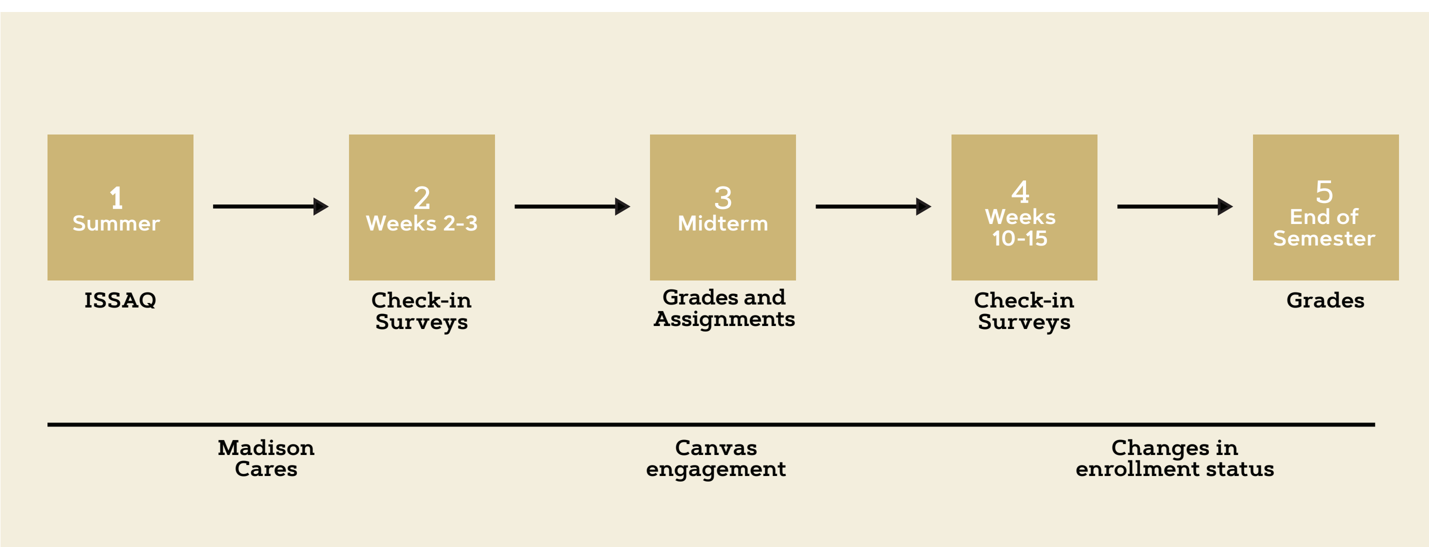
- ISSAQ survey data: student-reported survey data across 12 non-cognitive factors as students on-board to JMU
- Check-in survey data: student-reported survey data that checks in on students throughout the semester across four factors
- Midterm grades: faculty-reported data submitted based on students' grade performance at the mid-point of the semester
- Semester grades: faculty reported data submitted based on students' grade performance at the end of the semester
- Madison Cares referrals: individually reported data that refers students for follow-up by the Dean of Students office for any reason
- Canvas LMS data: Libraries-reported data from the Canvas LMS based on student activity, engagement, and grade performance in each class
- Student status: Registrar's Office-reported data indicating when students drop from full-time student enrollment status (12 credit hours or more) to part-time student enrollment status (11 credit hours or fewer).

The technology for the ESSS is based on a CRM[1] that enables communication, case management, referrals, dashboard creation, data collection, and other collaboration across campus.

Figure 1 demonstrates the anticipated timeline in the first iteration of the system, assuming students initially enter JMU for the fall semester. Data streams within the boxes represent moments in time; the data streams underneath the line (Madison Cares, Canvas engagement, Changes in enrollment status) represent actions that may occur at any time, all the time. This timeline would restart each semester, so students beginning spring semester would receive the ISSAQ as part of their orientation and on-boarding during late December or early January.

[1] Acquisition of a customer relationship management system and its integration into the JMU culture are parts of the Reengineering Madison initiative. On Jan. 26, 2023, Salesforce was awarded the CRM contract. More information is included in Appendix C.

**Figure 1. Early student success system semester timeline**



## Personnel

Early Success & Enrollment Analytics Team: The early success and enrollment analytics team will design, build, and oversee the early student success system; facilitate early student support across campus from data-informed insights; and help lead equitable student success and retention initiatives across JMU. The team includes the following new positions and will report to the Vice Provost for Student Academic Success & Enrollment Management:

- Director
- Data Scientist (2)
- Student Success Coordinator (2)
- Data Engineer

**Adviser Positions:** Advisers play an essential role in the day-to-day and individual approach to student success and retention. Four new adviser positions are requested across five years to help provide additional advising support for students and reduce adviser/student caseloads.

**Retention Committee:** The retention committee is a new university-wide committee that would help ensure that retention efforts across the institution are aligned, with divisions collaborating, sharing data, frequently communicating, and facilitating the use of best practices for equitable student success and retention. The retention committee would be co-chaired by leaders within Academic Affairs and Student Affairs.

**Data Committee:** The data committee is a new university-wide committee that would help strategize for the equitable collection, use, and communication of data to inform decision-making and programming across campus, particularly related to student success and retention.

## Process

### Overall Design Process

In summer 2021, a QEP Working Group was assembled, consisting of 20 faculty, staff, and graduate and undergraduate students who were nominated or volunteered during the search for "members with interest and enthusiasm for student support and progress, as well as a history of supporting JMU's diversity, equity and inclusiveness goals." The QEP Working Group began formally meeting during Fall 2021 and focused on researching and designing an early alert system (EAS) that would address the equity-based retention gaps and increase overall retention at JMU. Early working group discussions recognized the possible negative outcomes of a data-analytics system targeting social equity and that the ethical implementation of such a system would require an ethical design process. As a result, the QEP WG applied an equity-minded design through its adoption of its SETI values and the AIRR framework (Culver, Harper & Kezar, 2021).

The working group first adopted an equity-minded orientation with four guiding values (SETI) as defined below:

1. Student-Centeredness: As beneficiaries/stakeholders, students should be included and regarded as experts in the creation process (Brown Wright, 2011; Serin, 2018)
2. Equity: Nebulous systems of power and oppression exist and must be actively critiqued and opposed in our work (Watt, 2015).
3. Transparent: The practice of keeping the public informed of conversations being had and decisions being made is important and required.
4. Improvement-minded: Application of the three steps of learning improvement: assess, intervene, reassess (Fulcher & Prendergast, 2021; Fulcher et al., 2014)

These values were formed based on the perspectives and values of working group members as well as in response to the needs and wants of stakeholders, including students, faculty, staff, and administrators.

The QEP WG's initial work was guided by the SETI values. As a result of the literature research conducted in Fall 2021, the working group discovered the AIRR framework (Stilgoe et al., 2013) and elected to apply it as a more formal framework to guide the project.

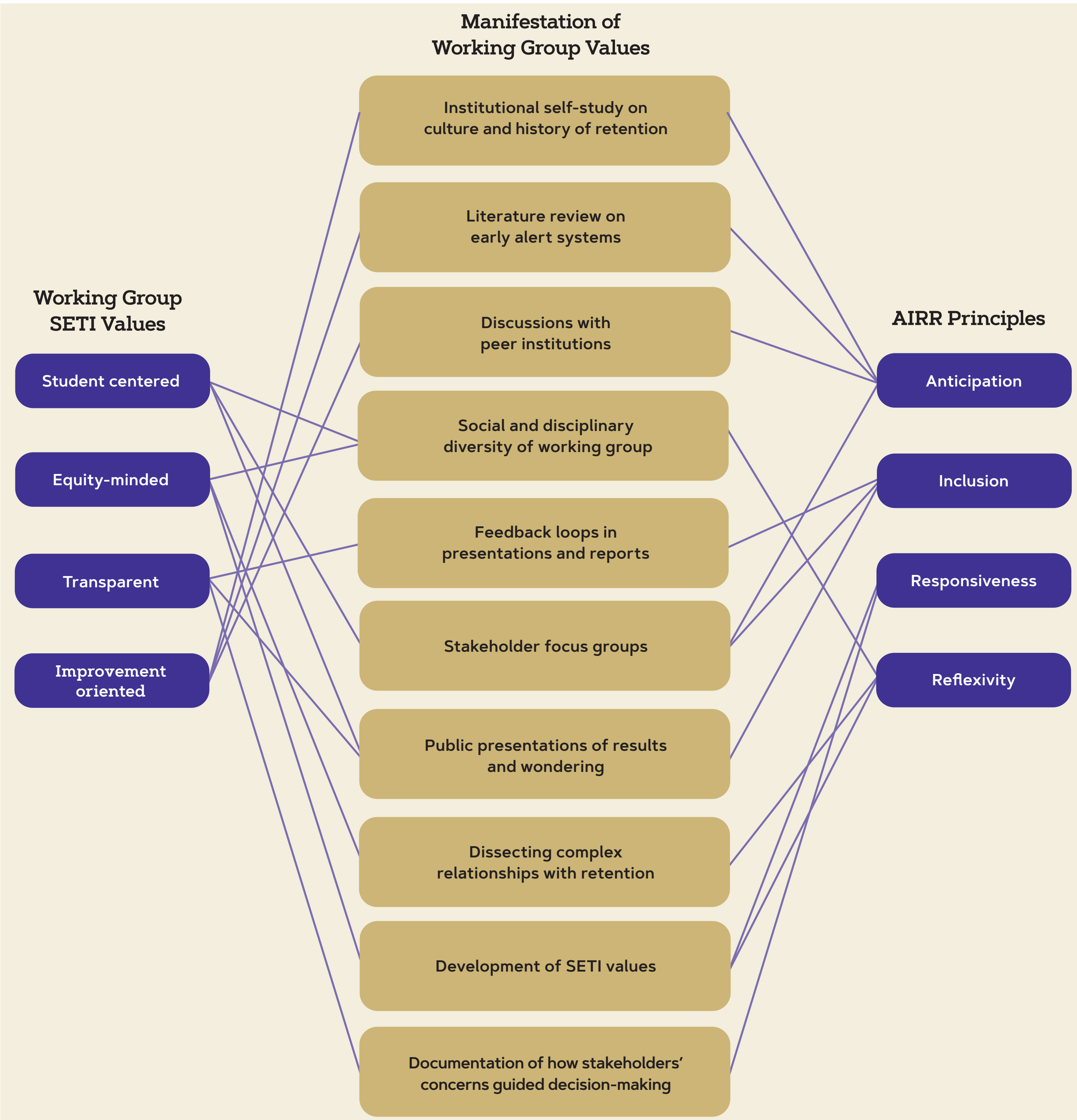
PHOTOGRAPH BY ELISE TRISSEL

The AIRR framework has been applied in science and technology fields as a framework for responsible innovation, with the letters of the acronym each representing an evidence-based practice that creates a more equitable and ethical design process:

- Anticipation: foreseeing consequences to design and implementation decisions
- Inclusion: engaging with all relevant stakeholders and allowing stakeholders to question innovation, design and implementation, as well as group processes
- Reflexivity: addressing stakeholder concerns and integrating stakeholder ideas into group processes, product design, and implementation
- Responsiveness: the practice of positioning one's social identities and values with the project and realizing that each singular positioning is limited

Figure 2 depicts the relationship between the SETI values and AIRR framework and how these values and practices were implemented in the working groups' research and design process (Patterson et al, in press).

**Figure 2. Mapping of AIRR Principles to SETI Values**



## Overall Research Process

During the 2021-2022 academic year, the QEP Working Group conducted research that included an examination of institutional data, stakeholder focus groups, consulting leaders at peer institutions, and a review of the literature on equitable student success and retention, early alert systems, and the use of data analytics in higher education. Working group members divided into sub-groups focused on each of these research tasks while continuing to regularly meet as a whole to share research updates and insights and to collaborate on research questions. A summary of research findings follows.

## Literature Review

The literature review sub-group worked to identify and analyze existing literature and scholarship related to the ESSS QEP, including equitable student success and retention, data analytics, learning analytics, early alert systems, data privacy, and data governance. Their research generated an annotated bibliography and two drafts — one on implementation considerations for learning analytics and big data and a second on values and ethics to guide the system development. These documents served as critical resources for the work done by other sub-groups and informed the frameworks and values of the QEP WG moving forward, including the identification and adoption of the AIRR framework.

## Annotated Bibliography Excerpt

In working through the extensive literature, the QEP WG research literature subcommittee identified three critical areas of the early alert design process: values and ethics, learning analytics and big data, and responses and interventions in support of equitable outcomes. They decided to capture "everything else" in an annotated bibliography as much of the research covered topics not covered in separate reports yet could be relevant to the work moving forward. The annotated bibliography is organized into the following topics:

- Predictive Analytics: Overarching Resources
- Preparing for & Enacting Institutional Change
  - Institutional Readiness for Change
  - Approaches to Enacting Institutional Change
- Situating Early Alert within a Multi-dimensional, Institutional Approach to Justice, Equity, Diversity, and Inclusion
  - Institutional Policy Needed in Support of Student Success
  - Completion Outcomes Are Impacted by Representation
  - Fairness and Institutional Communication to Students May Impact Persistence
  - The Importance of Collecting and Connecting Comprehensive, Disaggregated Data
- Increasing Accuracy and Transparency in Predictive Models
- Promoting Agency: The role of Faculty, Advisers, and Students in LA Design & Intervention
  - Engaging Students
  - Engaging Advisors and Faculty
- Ethical Considerations in Learning Analytics
- It's Only As Good As How You Use it: Best Practices in Student Success to Inform Intervention
  - Strategies for Learning: Metacognitive, Motivational, etc.
  - The Importance of Addressing Well-Being and Promoting Help-Seeking
  - Leveraging the Power of Networking: Professional Networks and Peer-to-Peer Networks
  - Designing and Refining Interventions Based on Predictive Models
- Other Resources

## Value and Ethics Excerpt

The Early Alerts system is intended to identify students who may be at risk of withdrawing from the institution to support interventions that would increase retention rates and closing equity gaps. As such, it will integrate multiple forms of student-generated data, and this data will necessarily be identifiable. To design and implement such a system in ways that protect student privacy and well-being, and that promote JMU values, will require care and commitment throughout the design, implementation, and deployment phases.

The Early Alerts system can be understood as one form of learning analytics, which refers to "'the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing [sic] learning and the environments in which it occurs'" (Jones, 2019, 2, quoting Long & Siemens, 2011, 33). In the case of Early Alerts, the focus is not on classroom learning per se, but the entire learning environment—the campus—within which students' academic process is linked to a number of other factors in the context of retention. In this sense, it can also be understood as institutional analytics, or an institution-wide analytics system that enables administrators to access data and dashboards to track students across individual courses and to compare students (Jones, 2019, 4). Because systems geared toward retention may be designed to incorporate a wide variety of data, from classroom-based learning analytics to enrollment data to social media analytics, this section will use the umbrella term of "data analytics", which should be understood in this context as data analytics implemented and used by the university.

Effectively implementing an ethical data analytics benefits from an ethical design process. This section recommends an evidence-based framework for responsible innovation that highlights four distinct categories of praxis: Anticipation, Inclusion, Responsiveness, and Reflexivity (AIRR) (Owen, et al., 2013). While the AIRR framework has been applied to many different areas related to innovation and technology, from genetically modified crops (MacNaghten, 2016) to STEM education (Tomblin and Mogul, 2020), to our knowledge it has not been applied to help universities navigate the complex challenges related to responsibly developing and implementing data analytics. One affordance of the AIRR framework is that it translates easily across the diverse group of actors and stakeholders that are involved in such projects, it is broad enough to be tailored to institutional needs, and it aligns with well-established practices for stakeholder-engaged development of projects and programs within a university setting.

One question for this system, then, is how it can achieve its goals while supporting student agency and avoiding harm. According to Prinsloo and Slade, "Student-centered learning analytics proceeds from the basis that students are not data-providers or data-points, but that they are and should be involved in determining what data would be valuable for them to make better informed decisions within their loci of control" (Prinsloo and Slade, 2018).

Could an early alerts system be designed not just to enable appropriate interventions, but to support student learning and agency in relation to their own success at JMU?

## Recommendations:

1. Define an institution-wide set of principles and policies concerning learning analytics at James Madison University and make these publicly accessible
2. Frame 'Early Alerts' as a student-centered success support system that foregrounds student agency and utility in supporting their own learning and success
3. Proactively educate students on the benefits and risks of learning analytics, as well as their rights with respect to data usage at JMU
4. Identify which data should be opt-in, which should be opt-out, and which should be neither. These decisions should be documented and should be aligned with the stated principles and policies
5. Document all design decisions with rationales
6. Implement a plan for evaluating and monitoring the system once it is live

## Learning Analytics & Big Data Excerpt

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

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

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

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

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



PHOTOGRAPH BY JUDAHPRAISE ACHEAMPONG

## Institutional Data Research

The institutional data sub-group worked with the Office of Institutional Research and the Office of the Registrar to generate a data set of all students over the last five years for the purpose of identifying trends related to equitable student success and retention at JMU (see Appendix D). The resulting data set consisted of 28,556 students who attended JMU between Spring 2017 and Fall 2021. Using this data set, the sub-group sought to answer three questions:

1. What portion of students leave JMU?
2. When are students leaving JMU?
3. Why do students leave JMU?

Analysis of this data set showed that although not many students leave JMU (8.2% of students who enrolled over the past five years) as compared to peer institutions, there is disparity in the proportion of students leaving JMU by identity groups and there is insight that can be gained on when and why students leave JMU. The data show that students may leave JMU at any point, though over half of those who left did so in their first two years. Analysis of reasons why students leave JMU revealed three key points, as shown in Table 1:

- Mental health is a top concern for all students, regardless of identity.
- Historically marginalized students are more affected (proportionally) by finances and sense of belonging.
- Academics alone are rarely a point of worry for students who choose to leave JMU.

**Table 1. Reasons students have left JMU (Spring 2017-Fall 2021)**

| Reason | Frequency | Percent |
|---|---|---|
| Transfer | 230 | 15.7% |
| Psychological | 204 | 14.0% |
| Leave of Absence | 190 | 13.0% |
| Fit/Belonging | 157 | 10.7% |
| Health | 136 | 9.3% |
| Personal | 115 | 7.8% |
| Finances | 105 | 7.2% |
| Home | 79 | 5.4% |
| COVID | 65 | 4.4% |
| Family | 59 | 4.0% |
| Medical | 48 | 3.3% |
| Academics | 35 | 2.4% |
| Job | 20 | 1.4% |
| Major/Program of Study | 19 | 1.3% |
| Extenuating | 4 | 0.3% |

Together, these results indicate two key ideas:

- JMU would benefit from a system that is suited for at least the first two years, though there would be no harm in a system that addressed the whole student life cycle
- Given that noncognitive factors can often lead to poor academic performance and ultimately the decision to leave JMU, JMU would benefit from a system that targets students when they first report struggles in the identified noncognitive areas.

## Peer Institution Research

The peer institution sub-group conducted interviews with colleagues at three peer institutions (George Mason University, University of North Carolina – Asheville, and Ohio University) on questions relating to early alert systems, interventions for closing equity-based success and retention gaps, and the use of data analytics for student success. Later, the QEP Director also conducted site visits to Virginia Tech and Georgia State University. All institutions were selected based on their history of success regarding early alert systems, data analytics, and/or equity-minded student success initiatives; contacts at these institutions; or similarities in terms of size, student body, or institution type.

Insights from these conversations contributed to both changes in the design process and recommendations for the first phase of the Early Student Success System. For example, colleagues at several institutions made it clear how important it was to collect student-reported insights as students started their college career. Colleagues also shared some of the concerns and opportunities that arose when starting a new CRM or EAS (early alert system) with an outside vendor, such as the ability to access raw data, to customize, and to leverage national trends or benchmarks with their other clients. Later conversations enabled colleagues to provide feedback on the system elements the QEP WG was piloting and proposing, as well as the construction of the early success and enrollment analytics team.

## Focus Group Research

The focus group sub-group coordinated and conducted a total of 37 focus groups that engaged 132 stakeholders, including faculty, staff, administrators, and students. The purpose of the focus groups was two-fold: 1) to engage stakeholders in the process of designing and implementing an EAS and 2) to gather information about the needs and perspectives of stakeholders to inform the design.

Through analysis of the focus groups results, the working group gained a better understanding of stakeholders' perceptions of retention at JMU and institutional readiness and responsibility to ethically implement an EAS targeting social equity. Furthermore, the importance of student agency, system integration and usability, and continued stakeholder engagement was elevated. Focus group participants made it clear that there is:

1. a lack of community and cohesion primarily felt by targeted student segments;
2. no clear understanding of existing student resources/services and a perception that JMU is not sufficiently resourced to be able to offer the necessary assistance to all students who may need it; and
3. a desire for a system that provides access to meaningful data and information so long as any system prioritizes ease of use and student agency.

As a result of this research, it was recommended that the QEP WG and university leaders consider the readiness of JMU to commit to the infrastructure, cultural, and policy changes needed to support such a system. Results also supported the importance of noncognitive factors, such as student engagement and sense of belonging, on student success and retention.

In summary, the QEP WG identified four main factors (well-being, basic needs, sense of belonging, and academics) that explained why most students left JMU and were thus the areas where an early student success system would need to gather data to generate insights for connection and intervention. The working group came to these conclusions based on the research conducted via literature review, institutional data analysis, talking with peer institutions, and through focus groups. The group determined that the next step was to try to design an early student success system that aligned with and mapped back to these research findings.

These four main factors were also later validated externally by the findings of three different student success reports. First, the JMU campus climate study, conducted by Rankin & Associates Consulting, identified sense of belonging, lack of diversity, mental health, disability, academic concerns, and self-efficacy driving student experience of a cooler campus climate, both overall and along various equity-based segments. Second, the State Council of Higher Education for Virginia's (SCHEV) "What Matters Most" report identified four factors impacting student success; college life/preparedness, sense of belonging, basic needs, and mental health and well-being. Third, the Boyer 2030 Commission Equity Imperative argued that equity and excellence were intertwined and advocated for accessible high impact practices and pro-active, holistic advising.

## System Design Process

At the end of the Spring 2022 semester, the working group shifted from a focus on research to beginning the design process. Based on the research evidence and institutional context, and in alignment with the adopted framework, they identified four key pillars of design for the first phase of designing the Early Student Success System: 1) data ethics, transparency, and communication design, 2) Incoming Student Skills & Attitudes Questionnaire (ISSAQ non-cognitive student survey), 3) student check-in surveys, and 4) rethinking mid-term grades.

### Data ethics, transparency, and communication

This design sub-group began work to identify the principles, values, and frameworks that will guide the design and implementation of the Early Student Success System. Their work has included a review of existing JMU policies and procedures, principles, and language guiding learning analytics use and implementations at other universities. From this review, this sub-group plans to make recommendations for the ethical use of data analytics at JMU, including a communication plan for how students can opt-in/out of their data collection and use. The group identified the values created within Reengineering Madison as a good starting place for the QEP work to align (Figure 3).

**Figure 3. Reengineering Madison Values**

| **Student Focus** | **Equity** | **Transparency** | **Community** | **Responsibility** |
|---|---|---|---|---|
| We will focus on student needs as we implement new technologies. | Our practices will ensure equity and inclusion across the institution. | We will promote understanding, data sharing, and open exchange in our practices and the systems we build. | We will develop new partnerships and strengthen existing collaborations for the greater good. | We will educate our constituency on data privacy and stewardship. We will take collective responsibility for the security of our data. |
| **INTEGRATION** We are committed to a campus where technology and data are integrated and shared | | | | |
| **Simplification** | **Standardization** | **Transformation** | **Quality** | **Continuous** |
| We will seek efficiencies including reducing steps and time involved in our business processes. We will not let the perfect be the enemy of the good. | We will change how we work. Out-of-the-box, best practice processes and functionality provided with cloud systems will be utilized. | The design of our future state will not be constrained by current business processes. | We are focused on high-quality, humane, and evidenced-informed practices driving reliable data. | We will assess and refine our processes and systems as we learn about issues and ideas from users and the wider higher education landscape. |

## Incoming Student Skills & Attitudes Questionnaire (Fall 2022 pilot of ISSAQ non-cognitive student survey)

The Incoming Student Skills & Attitudes Questionnaire (ISSAQ) is a survey, developed by DIA Higher Education Collaborators, that measures student aptitude on 12 noncognitive factors that address the behavioral, motivational, emotional, and social domains of student success. The ISSAQ was initially administered to new JMU students in Fall 2020. The data collected from the first pilot in Fall 2020 was used to generate a student success index specific to JMU for use with students beginning Fall 2022, identifying four factors that influenced the probability of student success in their first semester and first year at JMU. The four factors are (Appendix E):

- Organization
- Engagement
- Goal Commitment
- Sense of Belonging

Because of the elevation of the importance of noncognitive factors during the research phase of this initiative, the working group collaborated with JMU Orientation and Transition and University Advising to administer the assessment with all incoming first-year and transfer students during their Summer 2022 orientation. A total of 4,703 unique survey responses were generated (approximately a 91.8% completion rate).

Students received a copy of their report in August, and advisers received a roster view of their students' scores in September. The student report reminded students that knowledge and attitudes change, that seeking help is encouraged, and then shared resources mapped onto each factor, enabling students to seek out support and growth. The adviser report provides factor-by-factor score for each student and also provides the student success index status according to those four validated factors. In Fall 2022, advisers were encouraged to use that information to prioritize outreach and support to advisees.

## Student Check-In Surveys

Student success literature and results from the focus group study both highlight the importance of the first six weeks of a student's first semester. Midterm grades, which are issued in the seventh week, are currently the first formal insight into student progress and engagement. JMU has some systems, such as Madison Cares, that help to identify students in need of assistance. However, midterm grades and other systems are perceived as reactive and often occurring too late.

In the Fall 2022 semester, this sub-group piloted brief check-in surveys that were sent to first-year students (via text using Signal Vine) in the second and fourth weeks of the semester. These surveys literally checked in on four critical areas: basic needs, well-being, academics, and sense of belonging (Table 2). Additionally, students were texted a single question they could respond to with a Likert scale following fall break and prior to spring registration. Both the surveys and texted questions gave students the option to be connected to an individual or resource on campus that could assist with any needs they shared. Only if students indicated this were they asked to share their identity and contact information; otherwise, their data was collected in aggregate.

**Table 2. Select responses from week two & four check-in surveys at residence hall (n=419)**

| Week 2 Statements | % of respondents (43/47) |
|---|---|
| I made the right choice to attend JMU. | 81% agree |
| I can manage my time and stay organized. | 77% agree |
| I am not sure if I will have housing or access to food over break. | 79% disagree |
| I have received needed accommodations to be successful at JMU. | 16 people agree, 5 people disagree |
| I have been experiencing a level of stress, anxiety, or sadness that has been difficult for me to manage. | 49% agree, 18 people disagree |
| | |
| **Week 4 Statements** | **% of respondents (16/17)** |
| I feel that I belong at JMU. | 72% agree, 2 people disagree |
| JMU is welcoming to students of all backgrounds. | 88% agree |
| I am satisfied with student orgs offered at JMU. | 88% agree |
| I have at least one class I am worried about passing. | 63% agree, 5 people disagree |
| I have had interactions with faculty outside of the classroom. | 56% agree, 7 people disagree |
| I am certain that I will complete my degree at JMU. | 88% agree |

During the texting pilot after the mid-point of the semester, the results were a bit more favorable than expected. For instance, the use of texting was feared because of concerns that students would opt-out at a high rate. Of the 419 within the sample, only seven opted out of receiving the texts. Forty-eight students responded to the micro-survey about feeling ready for enrollment and registration, more than the number of students who responded to the first check-in survey email during week two. Moreover, students were grateful and used emoticons to convey that they were enjoying the engagement.

## Rethinking Midterm Grades

Currently, midterm grades are issued only to first-year students shortly before the mid-semester withdrawal deadline. Assignment of midterm grades are an expectation rather than a requirement for faculty at JMU, and they are only intended for students with fewer than 28 credit hours. Though midterm grades are a conventional indicator of academic progress in a course, issues with the current midterm grade system at JMU were widely discussed during QEP Working Group focus groups conducted in the research phase. In particular, faculty and academic advisers expressed concerns about the lack of reliability, consistency, meaningfulness, and timeliness of midterm grades as a method of gauging student progress. During Fall 2022, about 74% of all students eligible to receive a midterm grade received one. Despite concerns, there was recognition that some meaningful system for reporting student progress should exist as a part of an early alert system. A desire was also expressed for the system to be scalable, to include more than just new students.

During Fall 2022, this sub-group began researching other models of midterm grading and progress reports used by special populations at JMU (e.g., Athletics, Centennial Scholars) and at other universities. The sub-group also continued to work to understand the perceptions of midterm grades at JMU by surveying academic unit heads. The survey asked academic unit heads to seek the consensus of their faculty, regardless of whether faculty currently report/use midterm grades or not, and then complete the survey. The data revealed two key insights:

1. There seems to be a lack of understanding among faculty of the benefit of midterm grades to students, relative to the cost to instructors.
2. Midterm grades should be a developmental opportunity that provides students with information that empowers them to interpret and act on their current progress.

The sub-group has identified alternative models of midterm grading that center student agency, empowerment, and development, which will be piloted in the spring 2023 semester with faculty and advisers who primarily teach/advise new students.

PHOTOGRAPH BY GRACE ZACHARIAS

## Timeline

Establishing the anticipated timeline was given high priority for multiple reasons. First, it helped to establish target goals for developing the system, having the team in place, and being able to reach student success outcomes appropriately aligned. Second, it demonstrated how elements of the system, team, and outcomes are each scaled up slowly. This slow and scaffolded build is consistent with best practices identified in the literature and in consultation with peer institutions. It allows the team and institution to have enough time to gather evidence, learn from failures, and adapt to improve the system, collaborate on interventions, and re-allocate resources as necessary. Moreover, there was concern that rolling out the complete system at the start might be overwhelming in terms of changes in culture, expectations, resources, and systems. Third, establishing and communicating the timeline helped to build buy-in, credibility, and trust while simultaneously providing a mechanism for accountability.

Table 3 represents the anticipated timeline for rolling out the elements of the Early Student Success System. The timeline is intentionally conservative as the QEP Director and QEP WG acknowledge some of the significant challenges inherent in building out a home-grown institutional system. A major challenge was the unknown timeline for the university's CRM, an essential component as the technological backbone of the system. To accommodate this major unknown, the QEP WG has been testing and piloting different aspects of the system to better understand scale, scope, and impact. The elements selected aligned with data streams identified in the literature, by peers, and through institutional research at JMU, and the initial core elements of the ESSS can be administered manually with the requested team as the CRM is developed, implemented, and integrated into JMU.

**Table 3. Early student success system five-year plan**

| | 2023-2024 | 2024-2025 | 2025-2026 | 2026-2027 | 2027-2028 |
|---|---|---|---|---|---|
| **ISSAQ** | All incoming first-year and transfer students | All incoming first-year and transfer students | All incoming first-year and transfer students | All incoming first year and transfer students | All incoming first year and transfer students |
| **Check-ins** | Two dorms | Half of all first-year & transfer | All first-year & transfer | All first-year & transfer | All first-year & transform pilot expansion to rest of campus |
| **Midterm grades & Progress Reports** | Expected firsttime on-campus students | Expected firsttime on-campus students; open all students | Required firsttime on-campus students; open all students | Required first-time on-campus students; open to all students | Required first-time on-campus students; expected all students |
| **Semester grades** | All students | All students | All students | All students | All students |
| **Madison Cares referrals** | Early student success handles academic | Early student success handles academic | Early student success handles academic | Early student success handles academic | Early student success handles academic |
| **LMS Canvas Data** | Zero-activity report | Zero-activity report and explore other indicators | Zero activity and other indicators | Zero activity and other indicators | Zero activity, other indicators, and explore other interactions |
| **Full-time to Part-time Report** | All students | All students | All students | All students | All students |
| **Triangulation of data points & Insights** | | | Triangulation of data points & insights | Triangulation of data points & insights | Triangulation of data points & insights |
| **Other system developments** | | Explore other data streams, eg. curricular analytics, campus involvement | Integrate new and explore other data streams, eg. curricular analytics, campus involvement, admissions | Integrate new and explore other data streams, eg. curricular analytics, campus involvement, admissions | Integrate new and explore other data streams, eg. curricular analytics, campus involvement, admissions |

## D. RESOURCES

JMU has already committed significant resources to the ESSS QEP through initial budget approvals, including personnel, the technological commitment to the CRM, and the time and attention QEP efforts have received at all levels across campus. These resources have been critical for the QEP Director and QEP Working Group to initiate and accomplish the milestones to this moment.

The resource proposal for the next five years reflects the institutional commitment to implement and complete the ESSS QEP (Table 4). The QEP Director worked closely with the Associate Vice President for Academic Resources within Academic Affairs, Vice Provost for Student Academic Success and Enrollment Management, and University Budget Director within the Office of Budget Management to commit to ongoing planning and evaluation of resources given the QEP Working Group recommends an agile system and team, as well as the possibility that increased retention may also yield increased tuition revenues.

**Table 4. QEP Five-year Budget Proposal**

| | Year 0 | Year 1 | Year 2 | Year 3 | Year 4 | Year 5 | 6-year Totals |
|---|---|---|---|---|---|---|---|
| | FY 2023 | FY 2024 | FY 2025 | FY 2026 | FY 2027 | FY 2028 | |
| | | | | | | | |
| **Personnel** | | | | | | | |
| **QEP Director** | | 155,316 | 155,316 | 155,316 | 155,316 | 155,316 | 776,580 |
| **Data Scientist** | | 118,980 | 118,980 | 118,980 | 118,980 | 118,980 | 594,900 |
| **Student Success Coordinator** | | 100,811 | 100,811 | 100,811 | 100,811 | 100,811 | 504,055 |
| **Data Engineer** | | | 155,316 | 155,316 | 155,316 | 155,316 | 621,264 |
| **Data Scientist** | | | 118,980 | 118,980 | 118,980 | 118,980 | 475,920 |
| **Student Success Coordinator** | | | | 100,811 | 100,811 | 100,811 | 302,433 |
| **Advisors (1 FTE/Year)** | | | 86,277 | 172,554 | 258,831 | 345,108 | 862.770 |
| **Temporary Non -teaching salary** | 43,554 | | | | | | 43,554 |
| **Doctoral Assistant** | 0 | 18,348 | 18,348 | 18,348 | 18,348 | 18,348 | 91,740 |
| **Graduate Assistant** | 0 | 9,343 | 9,343 | 9,343 | 9,343 | 9,343 | 46,715 |
| **Undergraduate students** | 0 | 10,000 | 10,000 | 10,000 | 10,000 | 10,000 | 50,000 |
| **Research fellows** | 0 | 10,000 | 10,000 | 10,000 | 10,000 | 10,000 | 50,000 |
| **Equity champions** | 0 | 15,000 | 15,000 | 15,000 | 15,000 | 15,000 | 75,000 |
| **CSPA practitioner placement** | 0 | 5,000 | 5,000 | 5,000 | 5,000 | 5,000 | 25,000 |
| | | | | | | | |
| **Non-personnel** | 131,000 | 85,014 | 85,014 | 85,014 | 85,014 | 85,014 | 556,070 |
| **New position support** | 0 | 15,000 | 30,00 | 40,000 | 45,000 | 50,000 | 180,000 |
| | | | | | | | |
| **Re-Engineering Madison CRM Student Success/Advising** | 0 | 475,000 | 475,000 | 475,000 | 475,000 | 475,000 | 2,375,000 |
| **Totals** | 174,554 | 1,017,812 | 1,393,385 | 1,590,473 | 1,681,750 | 1,773,027 | 7,631,001 |

## Initiation

JMU demonstrated resource commitment to the QEP from the beginning through dedicated leadership, time, and personnel support. Senior leaders have been involved since the QEP topic selection process, with some serving on the QEP Director search committee; meeting regularly with the QEP Director; and providing opportunities for QEP awareness, collaboration, and advocacy. In committing to the QEP, leaders supported the search for a part-time QEP Director, served on and recruited for the working group, and provided budgetary support for graduate assistants to support and initiate the QEP. While permanent funding didn't exist for fiscal year 2022, the senior leaders identified funding where appropriate as the QEP Director and QEP WG made requests and recommendations for things like a survey pilot and travel related to research.

## Implementation

As the QEP Working Group researched and designed the ESSS and its team, the institution continued to commit significant resources toward the QEP. For fiscal year 2023, JMU provided the first permanent funding for the QEP, nearly $175,000. This new permanent budget would initially go toward temporary part-time salaries for the part-time director, graduate students, and undergraduate students.

Furthermore, the funds would support pilots like the non-cognitive survey distribution and analysis, use of a text messaging platform, and travel for conference and professional development opportunities. To fully begin implementing the ESSS QEP, the data scientist position was requested and approved early in the process because of its importance for data infrastructure and ecosystem development as JMU builds the system from the ground-up. The student success coordinator position was also hired initially because they will play a pivotal role by providing everyday support for the Early Student Success System. Also, hiring the student success coordinator early enables that person to build relationships across campus and cross train with colleagues in the Dean of Students Office as they will work closely together on student case management and establishing communication between the ESSS and Madison Cares.

The budget proposal makes permanent a director line to lead the early student success team and be an advocate for equitable student success and retention across campus as well as requests permanent graduate student support, with both a doctoral student and graduate student requested. In addition to the funds for personnel within the permanent budget, the allocation included non-personnel funds to support continued use of the non-cognitive survey, texting platform, conference travel and professional development, research and pilot programs, and position support.

## Completion

To make progress toward leveraging the ESSS toward increasing retention rates and closing equity-based retention gaps over the next five years, the budget proposal requests additional personnel support over the next five years. The request for a data engineer, second data scientist, and student success coordinator is included early in the budget proposal in anticipation of the scaling this new initiative, but also recognizing that adjustments might be made based on what is accomplished within the first year and what the ESSS team learns from the data insights. Furthermore, the request for four dedicated advisers to help with the anticipated increased advising and student success support load is staggered across the five years to use the time, data, and insights generated early on to inform and influence later budget requests.

PHOTOGRAPH BY STEVE ADERTON ('19)

## E. ASSESSMENT

The proposed assessment plan includes observing, benchmarking, and using the results of formative and summative direct and indirect measures to determine the efficacy of the Early Student Success System. Moreover, insights will be used to make changes along the way to improve equitable student success and retention at JMU. While JMU and other higher education institutions are still identifying what new enrollment and retention trends are poised to occur after the COVID-19 online pivot during the spring 2020 semester and the anticipated enrollment cliff (Grawe, 2018), Table 5 represents JMU's current retention baseline and targets over the next five years specifically for the QEP.

Note that the targets over the next five years focus particular attention on raising the retention rates for specific student populations that are currently experiencing lower retention rates than the overall student body. Retaining 20% more of the currently unretained students within these identified student groups will also increase the overall student body retention by 2%. This section will describe what measures are used to assess student success as well as how they will be implemented.

**Table 5. QEP retention direct measure assessment baseline and targets**

| | 2022-2023 | 2023-2024 | 2024-2025 | 2025-2026 | 2026-2027 | 2027-2028 |
|---|---|---|---|---|---|---|
| | **Year 0** | **Year 1** | **Year 2** | **Year 3** | **Year 4** | **Year 5** |
| | Benchmarking | Benchmarking | Direct measure goal | Direct measure goal | Direct measure goal | Direct measure goal |
| **Overall Retention** | 89.2% | TBD | 89.6% | 90.2% | 90.2% | 91.2% |
| **Black students** | 84.9% | TBD | 85.7% | 86.4% | 86.4% | 87.9% |
| **First-Gen students** | 83.1% | TBD | 84.0% | 84.8% | 84.8% | 86.5% |
| **Hispanic students** | 86.8% | TBD | 87.5% | 88.1% | 88.1% | 89.4% |
| **More than 1 race/ ethnicity students** | 84.8% | TBD | 85.6% | 86.3% | 86.3% | 87.8% |
| **Out of state students** | 87.3% | TBD | 87.9% | 88.6% | 88.6% | 89.8% |
| **Pell-eligible students** | 88.5%(2020) | TBD | 89.1% | 89.7% | 89.7% | 90.8% |
| **Transfer students** | 79.8% | TBD | 80.8% | 81.8% | 81.8% | 83.8% |

## Direct Measures

Undergraduate student retention is the most direct measure of student success addressed within the ESSS QEP, with student retention defined as the percentage of first-time students entering JMU that return the following fall. At JMU, first-time student retention is calculated separately from transfer-student retention, though both are important for the institution and ESSS. Overall undergraduate student retention is one direct measure that is included in the QEP assessment plan, where the overall undergraduate student retention rate is a singular number representing the entire first-time, first-year cohort. To get a more accurate measure of student success and retention, we also disaggregate retention rates among various social identities.

Disaggregated retention rates of specific student populations are another direct measure included within the assessment plan. As the goal is not just to increase retention rates, but also identify and close equity-based retention gaps, the assessment plan is particularly focused on the retention rates of those specific student populations that have been identified as having observably larger gaps with the overall undergraduate student retention rate. This group represents a reasonably large number of students within the student population group, and evidence-informed reasoning as to why that student population leaves JMU could arguably and successfully impact that group's retention rates. Through disaggregation of retention data, JMU can learn which students are more likely to leave the institution. Combining this disaggregated data with other indirect measures, the ESSS team can learn why specific student populations might be more likely to leave JMU and intervene proactively.

Through disaggregating data via various social identities and further institutional self-study, we identified the following individual groups may benefit the most from the early student success system and QEP:

- Black students
- First-generation students (students whose parents did not obtain a four-year degree)
- Hispanic/Latinx students
- Multiracial students
- Out-of-state students
- Pell-eligible students
- Transfer students

These groups have been identified as having low retention rates when compared to the JMU student population (See Table 6).

**Table 6. Undergraduate student retention rates at JMU**

| | Overall | Black | First- Gen | Hispanic | More than 1 race/ ethnicity | Out of State | Pell-eligible | Transfer |
|---|---|---|---|---|---|---|---|---|
| **2013** | 92.4% | 87.1% | 91.3% | 92.3% | 93.2% | 89.4% | 91.5% | 86.1% |
| **2014** | 91.0% | 85.9% | 88.4% | 91.3% | 91.7% | 89.8% | 85.1% | 85.9% |
| **2015** | 91.2% | 87.4% | 89.2% | 92.8% | 94.1% | 89.3% | 87.5% | 86.4% |
| **2016** | 90.2% | 90.5% | 88.7% | 91.3% | 91.5% | 87.5% | 88.4% | 82.8% |
| **2017** | 90.3% | 87.2% | 86.8% | 85.5% | 90.3% | 88.8% | 88.3% | 84.9% |
| **2018** | 89.1% | 86.4% | 85.3% | 88.0% | 88.0% | 86.1% | 84.8% | 86.3% |
| **2019** | 89.0% | 88.9% | 84.2% | 88.4% | 87.1% | 85.0% | 86.5% | 85.9% |
| **2020** | 90.9% | 91.9% | 88.5% | 87.3% | 87.1% | 89.7% | 88.5% | 92.7% |
| **2021** | 89.2% | 84.9% | 83.1% | 86.8% | 84.8% | 87.3% | TBD | 79.8% |

PHOTOGRAPH BY JULIA WEAVER ('21)

In addition to identifying student groups experiencing retention rates lower than the overall student body, reporting results is an important factor in how action is taken. Scholars and practitioners alike recommend against comparing different historically minoritized student populations against a historically dominant student group (i.e., comparing Black student retention to white student retention; Castillo & Gillborn, 2022). Within the QEP assessment plan, different student retention rates are compared to the overall retention rate rather than another student group's rate. The proposed assessment plan will also report and benchmark each of the above student group's retention data against their own group's historical trends. This is done to avoid comparing socially marginalized to privileged groups, resulting in the creation of deficit-based reporting, and to control for the overrepresentation of certain groups, like white students, that may skew overall retention data.

Understanding and predicting retention rates, whether overall or for specific student populations, has proven difficult the last few years due to the COVID-19 pandemic and economic and other socio-political factors across American higher education (Conley & Massa, 2022). JMU is no exception as the Fall 2020 institutional retention rates, both overall and in most demographic groups, experienced an unanticipated increase. The slight increase in Fall 2020 retention rates appear to be an exception, as retention rates for 2021 decreased and returned to pre-COVID rates. The temporary increase in Fall 2020 retention rates could be due to changes in academic policies at JMU to accommodate extreme circumstances during the height of the COVID-19 pandemic. For example, JMU offered credit/no credit as a course grading option to more students. Next, almost no students were placed on academic suspension or probation. Furthermore, students who may have been impacted or reflected in lowering retention rates may have decided or not been able to attend JMU or pursue higher education during that time period because of health, family, or structural inequality reasons. While the Fall 2021 retention rates were disappointing because they represented a decrease from Fall 2020, their return to Fall 2019 trends provides more confidence in our ability to understand and predict retention rates moving forward. However, establishing and understanding retention rate trends during the next two to three years of the ESSS QEP and assessment plan will prove critical.

The assessment plan for retention rates as a direct measure focuses on benchmarking during 2023-24 (year 1) while establishing seemingly reasonable and accomplishable goals for increasing overall retention rates and closing equity-based retention gaps over the first five years of the early student success QEP (Table 7). The method used to establish goals for retention rates focuses on student count and retention rate to better understand what is needed in terms of more students retained to move the needle on retention rates. Please note that while all data referenced here assumes the Fall 2021 retention rates, Fall 2020 data for Pell-eligible students is used due to the complications and delay with reporting federal financial aid data.

**Table 7. QEP assessment retention rate goal benchmarking**

| | Sample Size | Retention Rate | Students not retained | Overall cohort | Overall retention rate | Current retention gap |
|---|---|---|---|---|---|---|
| **1st Gen** | 544 | 83.1% | 92 | 4770 | 89.2% | 6.1% |
| **Out of State** | 1009 | 87.3% | 128 | 4770 | 89.2% | 1.9% |
| **Hispanic** | 341 | 86.8% | 45 | 4770 | 89.2% | 2.4% |
| **Black** | 205 | 84.9% | 31 | 4770 | 89.2% | 4.3% |
| **Transfer** | 774 | 79.8% | 156 | N/A | 89.2% | 9.4% |
| **Pell-Eligible (2020 data)** | 616 | 88.5% | 71 | 4452 | 90.8% | 2.3% |
| **More than one race/ ethnicity** | 256 | 84.8% | 39 | 4770 | 89.2% | 4.4% |


Using first-generation students as an example to understand the method, their Fall 2021 group size was 544 and retention rate was 83.1%. This means that about 92 first generation students were not retained by JMU. If the Early Student Success System was able to help increase retention of unretained first-generation students by 5%, that would mean retaining about five first-generation students above and beyond those currently retained (Table 8). That reflects a 5% increase from the 92 first-generation college students not currently retained. That same method, based on the Fall 2021 retention data, is used such that a 10% increase retains nine more students.

**Table 8. QEP assessment retention rate projected targets increasing unretained students**

| | 5% increase | 5% retention rate | 5% retention gap | 10% increase | 10% retention rate | 10% retention gap |
|---|---|---|---|---|---|---|
| **1st Gen** | 5 | 84.0% | 5.7% | 9 | 84.8% | 5.3% |
| **Out-of-State** | 6 | 87.9% | 1.7% | 13 | 88.6% | 1.5% |
| **Hispanic** | 2 | 87.5% | 2.2% | 5 | 88.1% | 1.9% |
| **Black** | 2 | 87.7% | 4.0% | 3 | 86.4% | 3.6% |
| **Transfer** | 8 | 80.8% | 8.8% | 16 | 81.8% | 8.2% |
| **Pell-Eligible (2020 data)** | 4 | 89.1% | 0.6% | 7 | 89.7% | 0.4% |
| **More than one race/ethnicity** | 2 | 85.6% | 4.1% | 4 | 86.3% | 3.7% |

PHOTOGRAPH BY JULIA WEAVER ('21)

This method of calculating the number of currently unretained students, new retention rates, and equity-based retention gaps was used to project out to the five-year targets (Table 9 below). In analyzing the data, the QEP Director and QEP WG recognized that a reasonable five-year goal is increasing unretained student retention for each identified group by 20%, which would increase JMU's overall retention by 2%.

This method to project retention rates and set goals for the number of increased students retained has two limits currently. First, it assumes that there is no other impact on the retention rates of other student groups. While the increased number of students retained in the identified specific student group populations is taken into consideration for calculating a new overall retention rate, it holds all other student populations stable. For example, the 5% equity goal produces a new overall retention rate of 89.6% because about 21 new students are retained than are currently retained. This does not reflect increases in transfer students because they are not calculated currently as part of the overall rate of first-time students returning for the following fall semester.

This new overall retention rate for the 5% equity goal is then used against the new student specific retention rates for the 5% equity goal to identify a new equity-gap assuming the 5% equity goal is met. For example, using Fall 2021 retention data, there is an equity gap of 6.1% for first-generation students when taking the overall retention rate, 89.2% and subtracting the first-generation student retention rate, 83.1%. The equity gap decreases to 5.7%, assuming the 5% equity retention goal is met. This is calculated with the new overall retention rate for the 5% equity goal, 89.6%, and the new first-generation student retention rate, 83.9%, for the 5% equity goal. So, for first-generation students, within five years of the ESSS QEP, the goal is to retain about 18 more first-generation students each year. This would increase the first-generation retention to 86.5% and decrease the equity-based retention gap to 4.4%.

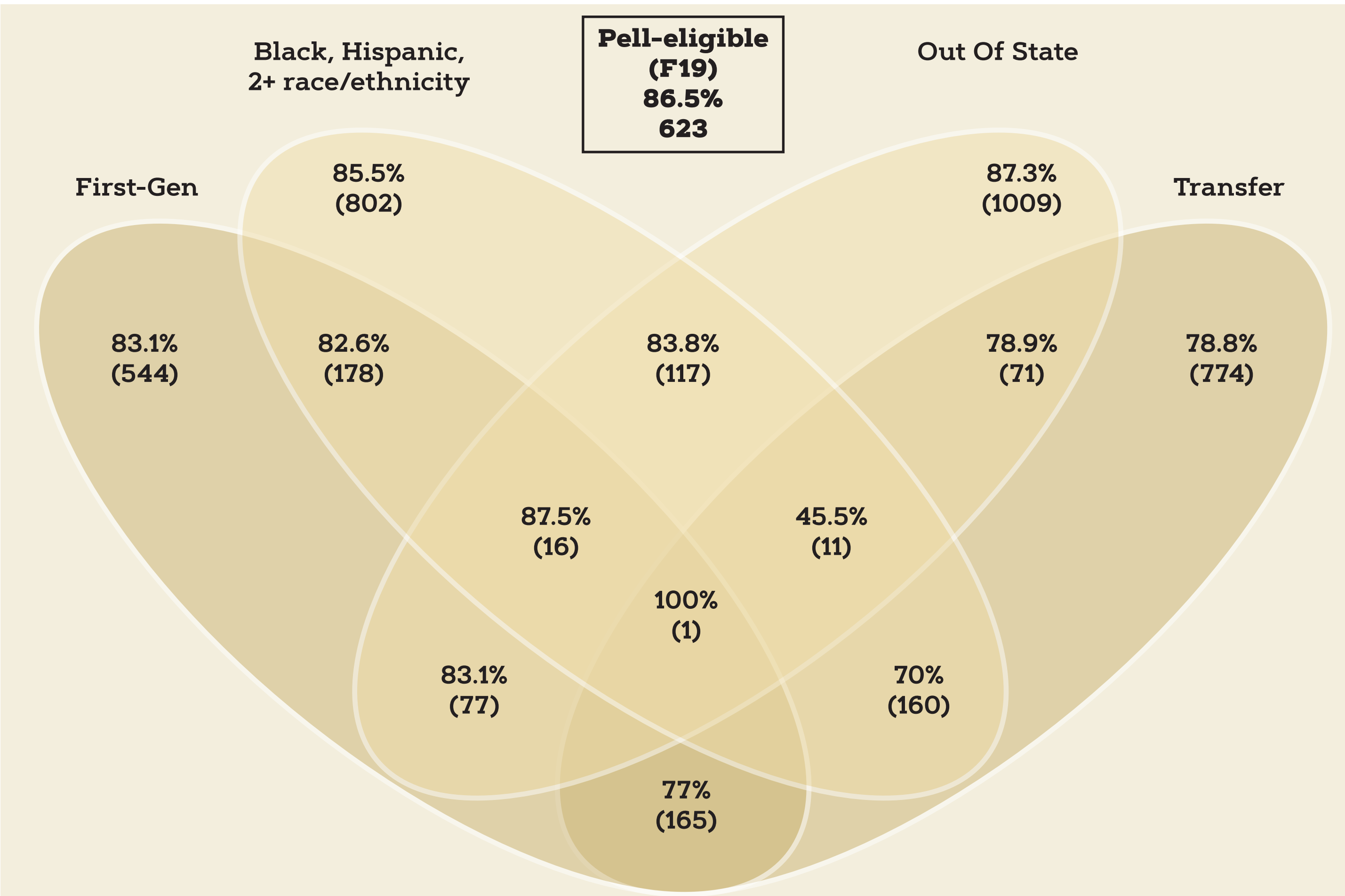
**Table 9. QEP assessment retention rate five-year targets**

| | 2022 - 2023 (Year 0) | | | | | 2027 - 2028 (Year 5) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Sample Size** | **Retention Rate** | **Students Retaineed** | **Equity Gap** | | **Retention Rate** | **Students Retained** | **Equity Gap** | **Increase In Students Retained** |
| **Overall Retention** | 4470 | 89.2% | 4255 | N/A | | 91.2% | 4350 | N/A | 95 |
| **Black Students** | 205 | 84.9% | 174 | 4.3% | | 87.9% | 180 | 2.9 | 6 |
| **First-Gen Students** | 544 | 83.1 | 452 | 6.1% | | 86.5% | 471 | 4.4 | 18 |
| **Hispanic Students** | 341 | 86.8% | 296 | 2.4% | | 89.4% | 305 | 1.5 | 9 |
| **More Than 1 Race/Ethnicity Students** | 256 | 84.8% | 217 | 4.4% | | 87.8% | 225 | 3.1 | 8 |
| **Out-Of-State Students** | 1009 | 87.3% | 881 | 1.9% | | 89.8% | 906 | 1.1 | 26 |
| **Pell-Eligibe Students (2020)** | 616 | 88.50% | 545 | 2.3% | | 90.8% | 559 | 0.1 | 14 |
| **Transfer Students** | 774 | 79.8% | 618 | 9.4% | | 83.8% | 83.8% | 7.1 | 31 |

Second, this method for calculating, projecting, and benchmarking retention rates is limited because it does not account for students' multiple, intersecting social identities (Figure 4). This method assumes each student is discrete, i.e., that a first-generation student is not also Black and out-of-state, etc. Of course, this influences the numbers and projections, but we believe the goals for specific student populations and overall retention rates are still obtainable because they build slowly and are reasonable over time.

For example, in examining the Fall 2021 retention rates for specific student populations, first-generation, out of state, Hispanic, Black, and more than one race students account for 2,355 students if we assume no intersectionality among identities. But in working with the Office of Institutional Research, we identified that if we do account for intersectionality, there are 1,998 unique individual students among these same demographic categories. Among first year students, this does not account for Pell-eligible students because that data lags one year. To increase the overall first year retention 2% over five years at the 2021 rates, we would need to retain about 95 additional students from these specific student populations to raise the overall retention rate, a reasonable goal within five years given the institutional commitment demonstrated in this QEP. Moreover, the ESSS team, alongside others at the university, will continue its work to identify additional ways to calculate retention rates that account for student intersectionality and adjust goals appropriately.

**Figure 4. Retention rates and sample population by intersectional demographic identity. Note retention rates shown are Fall 2021 with exception of Fall 2019 for Pell-eligible students.**




## Indirect Measures

Indirect measures collect data important for use in the evaluation of the ESSS QEP's success, but do not directly measure student retention or success. Our indirect measures capture data on things that either influence retention indirectly or are important measures to assess the early student success system, which itself has an indirect impact on student success and retention. Monitoring and observing these indirect measures may provide insights into things that can be changed or adapted to improve the Early Student Success System, leading to higher retention rates.

The indirect measures initially included in the assessment plan are included in Table 11. Note that many of the initial indirect measures align to the Early Student Success System. Early student success can only have the potential to be impactful if we are collecting, analyzing, and acting on data that provide snapshots of what students are thinking, doing, and feeling in a given moment. For instance, the early student success team needs students to complete the ISSAQ survey as they join the university community and for faculty to complete and submit midterm grades. Once this data is collected, the early student success team is able to generate insights that can be shared with advisers, faculty, practitioners, and others to act on to help students accomplish their goals. Like more direct measures, the goals for indirect measures have intentionally been established such that they build and increase over time along with the changes in cultural norms and institutional expectations. Examples of these flexible indirect measures include the midterm grade completion percentages (as norms about completion change) and adviser caseloads (as adviser lines are added and different frameworks or expectations for advising change across campus).

Finally, some indirect measures have been identified because their role in student success and retention is understood to be important, but more research and time is needed to better explain and benchmark. For example, a student's sense of belonging and growth mindset are well established as contributing to student success and retention (Tinto, 2022), but little research has been done at scale at JMU. The ISSAQ provides an avenue to pursue this research, align with programming interventions, and function as a benchmark, but will need to be developed during the early part of the ESSS QEP assessment plan. Student GPA and DFW rates are similar as they have been studied in some departments and colleges, but still more time is needed to research, create shared understanding, and generate support for setting appropriate goals for GPA and DFW rates as indirect measures.

## Assessment Responsibility

The Early Success & Enrollment Analytics Team, particularly the director, is responsible for tracking, analyzing, reporting, and using the assessment data collected to improve the Early Student Success System and collaborations with campus partners for impacting equitable student success and retention. Of course, the team will not work alone on these assessment efforts but will collaborate with colleagues across campus.

- The Office of Institutional Research will support and collaborate on student retention data direct measures.
- Departments within Academic Affairs and Student Affairs will support and collaborate on ISSAQ and check-in survey indirect measures.
- JMU Libraries will support and collaborate on the LMS Canvas data.
- The Registrar's Office will support and collaborate on midterm grades, semester grades, and student status (full-time to part-time) reports.
- University Advising and individual colleges will support and collaborate on advising indirect measures.
- The Center for Assessment & Research Studies and Information Technology will support and collaborate throughout the assessment plan given their roles and expertise on campus.
- Information Technology will support and collaborate throughout the assessment plan given their roles and expertise generally, but especially as they build out the CRM and early student success system.

**Table 10. QEP retention indirect measure assessment baseline and targets**

| | 2022-2023 | 2023-2024 | 2024-2025 | 2025-2026 | 2026-2027 | 2027-2028 |
|---|---|---|---|---|---|---|
| | Year 0 | Year 1 | Year 2 | Year 3 | Year 4 | Year 5 |
| | Benchmarking | Benchmarking | Indirect measure goal | Indirect measure goal | Indirect measure goal | Indirect measure goal |
| **ISSAQ response rate first year & transfer students** | 91% | ? | 91% | 92% | 93% | 95% |
| **First year student faculty midterm completion percentage** | 74.40% | ? | 80% | 85% | 90% | 90% |
| **Transfer student faculty midterm completion percentage** | N/A | ? | 50% | 75% | 90% | 90% |
| **Non first year/ transfer student faculty midterm completion percentage** | N/A | ? | 10% | 15% | 25% | 50% |
| **Check-in survey sample size** | 491 | ? | 2,500 | 5,500 | 5,500 | 8,000 |
| **Check-in survey opt-out percent** | 1.70% | ? | 10% | 15% | 15% | 15% |
| **Primary (professional) adviser caseload average** | 166-764 range | ? | TBD | TBD | TBD | 350 |
| **Faculty adviser caseload average** | 18- 202 range | ? | TBD | TBD | TBD | 35 |

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# Appendix A: QEP Working Group Membership

Femi Ayoola, Graduate student, Kinesiology

Kenn Barron, Professor of Psychology

Corey Hickerson, Professor and Graduate Program Coordinator, Communication Studies

Tracey Kite, Associate Director, Office of Parent Relations

Thomas Lavenir, Assistant Director, Center for Global Engagement

Jolie Lewis, Associate Director, Transfer Student Success

Kristi Lewis, Professor, Health Sciences

Paul Mabrey, QEP Director; Assistant Professor, Learning Centers & Communication Studies

Danielle Maxham, Academic Adviser, Computer Information Systems

Rob Olewine, Associate Director, Transition Programs

Trent Pace, Adviser, Exploratory Major

Chris Patterson, Doctoral student, Center for Assessment and Research Studies

Andy Perrine, Associate Vice President, Marketing and Branding

Samantha Prins, Dean, College of Science and Mathematics and Professor, Mathematics and Statistics

Dom Rodriguez, Assistant Dean of Students

Jeff Souder, Budget Director, Office of Budget Management

Tatjana Titareva, Gradute student, School of Strategic Leadership Studies

Alison Waide, Director, Information Systems

Linette Watkins, Professor and Department Head, Chemistry and Biochemistry

Emily York, Associate Professor, Integrated Science and Technology

# Appendix B: QEP Presentations, Updates, and Representation Across CampusMembership

| Date | Event/Audience | Date | Event/Audience |
|---|---|---|---|
| 5/8/2021 | QEP Meet and Greet | 4/22/2022 | Peer to peer |
| 8/5/2021 | COB Student Success | 4/28/2022 | Advising & Tech Forum |
| 8/16/2021 | SALT | 4/29/2022 | Advising & Tech Forum |
| 8/25/2021 | SSLT | 5/3/2022 | CFI |
| 9/7/2021 | PLT | 5/3/2022 | Advising & Tech Forum |
| 9/13/2021 | President's Cabinet | 5/6/2022 | Transfer Advisor Training |
| 9/14/2021 | LC | 5/17/2022 | FYA Training |
| 9/22/2021 | SSLT | 5/18/2022 | CFI May Symposium |
| 10/13/2021 | Academic Council | 7/6/2022 | Academic Council |
| 10/20/2021 | SSLT | 7/11/2022 | SALT |
| 11/5/2021 | General Education Council | 8/10/2022 | ISSAQ Transfer Advisor Training |
| 11/12/2021 | SCOM | 8/11/2022 | ISSAQ Transfer Advisor Training |
| 11/17/2021 | QEP Student Forum | 8/15/2022 | QEP at New Faculty Orientation |
| 11/19/2021 | BOV Brief Update | 8/16/2022 | ISSAQ First year Advisor Training |
| 11/29/0202 | QEP Student Forum | 8/23/2022 | QEP at Madison Advising Peers |
| 11/30/2021 | QEP Student Forum | 9/12/2022 | QEP at CRM Discovery Discussion |
| 11/30/2021 | SGA | 9/15/2022 | ISSAQ at JMU Workshops with DIA |
| 12/8/2021 | JMU SACSCOC Advisory Group | 9/19/2022 | President's Cabinet |
| 12/15/2021 | Peer to peer | 10/3/2022 | SGA AA Subcommittee |
| 1/14/2022 | CHBS Opening Faculty Meeting | 11/4/2022 | QEP at AUH Meeting |
| 1/26/2022 | SSLT | 11/18/2022 | BOV Full Update |
| 2/18/2922 | BOV Full Update | 12/9/2022 | Academic Admission Standards Committee |
| 3/2/2022 | Peer to peer | 12/12/2022 | Peer to peer |
| 3/13/2022 | Diversity Conference | 12/12/2022 | First year seminar discussion group |
| 3/26/2022 | Parent's Council | 1/11/2023 | QEP at AC Budget Initiative Retreat |
| 3/28/2022 | SGA | 1/24/2023 | PLT |
| 3/29/2022 | CFI | 1/24/2023 | Advising & Tech Forum Two |
| 4/20/2022 | ISAT 400 | 1/27/2023 | Academic Admission Standards Committee |
| | | 1/30/2023 | Advising & Tech Forum Two |

# Appendix C: CRM Announcement

JAMES MADISON UNIVERSITY

## Reengineering Madison

Members of the JMU community,

We are excited to announce a major step forward in the multiyear Reengineering Madison effort to dramatically transform our campus technology and platforms, modernize our systems, and streamline our business processes, all aimed at dramatically improving the student experience and our relationships with everyone in the JMU community. **The contract for JMU's university-wide Customer Relationship Management (CRM) platform has been awarded to Salesforce, with Huron Consulting Group as our implementation partner.**

JMU is taking an enterprise, campus-wide approach to our CRM implementation. Enterprise capabilities for departments will include items like communications management, case management and events functionality. Specific functionality to support Advancement, Advising/Student Success and Admissions activities will also be delivered via the Salesforce platform. Over the next several years, the CRM platform will be implemented iteratively across functional areas.

We invite you to visit the CRM page on our Reengineering Madison website for additional information about this project, which will transform how we communicate and engage with our constituents!

The process leading up to the Salesforce contract involved valuable input and dedication from partners across the university. We want to express our sincerest appreciation to everyone involved in the CRM process thus far, and we look forward to continuing to work together throughout this implementation and beyond in support of JMU's mission, vision and values.

Regards,

Robin Bryan, AVP IT, CIO
Bob Kolvoord, Dean of CISE
Reengineering Madison Steering Committee co-chairs

# Appendix D: QEP Institutional Data Team Progress Report

## Section I: Relevant Data Analyses

### *Data Collection*

Data collected for this report was collected from the Office of Institutional Research, as well as the Office of the Registrar. We would like to thank both offices in their work for providing us with the data needed to explore equity and retention on JMU's campus.

### Sample

The initial sample for this report consists of 28,556 students who attended JMU between Spring 2017 and Fall 2021. Data filtering was not performed on students with missing data. Rather, adjustments were made for analyses that will be discussed in the report. As a result, subsample numbers may not match perfectly. Table 1 breaks down the sample by race/ethnicity, gender, and first-generation status.

*Table 1. Breakdown of Sample by Identity*

| Group | Identity | n | % |
|---|---|---|---|
| Race | American Indian/Indigenous | 61 | 0.2 |
| | Asian-/American | 1442 | 5.1 |
| | Black/African American | 1443 | 5.1 |
| | Hispanic/Latinx | 578 | 2.0 |
| | Multiracial* | 2888 | 10.1 |
| | Pacific Islander | 46 | 0.2 |
| | White | 21387 | 74.9 |
| Gender | Female | 16443 | 57.6 |
| | Male | 12057 | 42.2 |
| | Other Gender Identity | 11 | 0.04 |
| Generation Status | Continuing-Gen | 23199 | 81.2 |
| | First-Gen | 3684 | 12.9 |
| | Unsure | 1673 | 5.9 |

### Question 1: What proportion of students leave JMU?

Of the 28,556 students that have attended JMU between Spring 2017 and Fall 2021, 2,326 have left for various reasons Therefore, 8.2% of students who enrolled in the past 5 years have left JMU. Table 2 gives a more representative picture of this proportion by race, gender, and college generation status.

Pacific Islander and white students have the smallest proportion of departure with 6.5% and 7.8% of Pacific Islander and white students leaving JMU in the last five years, respectively. American Indian/Indigenous students have the highest proportion of leaving JMU (14.8%), followed by Black/African American students (9.0%). Female students have a lower departure rate from JMU in the past 5 years (7.5%) than male students (9.0%) and students who identify outside of the gender binary (0%). Finally, proportionally more first-generation students have left JMU in the past 5 years (9.4%) than students who have at least one guardian with a college degree (7.3%).

*Table 2. Proportion Leaving JMU by Identity Group*

| Group | Identity | # Attended JMU | # left JMU | Proportion of attended that left |
|---|---|---|---|---|
| Race | American Indian/Indigenous | 61 | 9 | 14.8% |
| | Asian-/American | 1442 | 119 | 8.3% |
| | Black/African American | 1443 | 130 | 9.0% |
| | Hispanic/Latinx | 578 | 48 | 8.3% |

| | | | | |
|---|---|---|---|---|
| | Multiracial* | 2888 | 251 | 8.7% |
| | Pacific Islander | 46 | 3 | 6.5% |
| | White | 21387 | 1670 | 7.8% |
| Gender | Female | 16443 | 1237 | 7.5% |
| | Male | 12057 | 1086 | 9.0% |
| | Other Gender Identity | 11 | 0 | 0% |
| Generation Status | Continuing-Gen | 23199 | 1684 | 7.3% |
| | First-Gen | 3684 | 348 | 9.4% |
| | Unsure | 1673 | 294 | 17.5% |

*Note: We recognize that the multiracial student group is a highly diverse group, and should not be treated as monolithic. However, JMU recognizes students with multiple racial identities as "multiracial."

This information is mostly consistent with what to expect from higher education literature regarding retention at Historically White Institutions (HWIs). Knowing the proportion of students that have left JMU in the past 5 years, broken down by identity, helps the QEP group to identify retention as an equity issue. If retention was not an equity issue, then all groups, no matter how they were identified, would have the same retention rate as the overall rate (8.2%). We know this is not the case. More specifically, white students, a group that holds racial privilege, has a lower proportion than the overall rate, signifying that on average, a higher proportion of white students stay at JMU than almost any other racial group. First-generation students (students who are the first in their family to attend college) are historically known to leave institutions at a higher rate than peers who have a guardian with a college degree. The interesting piece for JMU is noting that proportionally more male students have left JMU than female students in the past 5 years. Although male students are slowly becoming more underrepresented on college campuses across the country, it is interesting to see that 1.5% more males than females have left JMU.

### Question 2: When are students leaving JMU?

Students can leave JMU at any point in their academic career. Over the past 5 years, 1,896 students have left JMU between their first and fourth year on campus. Table 2 shows the time point in which students left JMU over the past five years. Most students leave in the first year, with over half of all students who leave JMU leaving in either their first or second semester on campus (n=1,044). This is in line with research in higher education retention; most students who leave an institution are most likely to do it within their first two semesters. Most early-alert systems are built around the first year student experience for this reason.

There are still many students that leave in their second year (n=539), which still is in line with research. When a student stays at one institution through their second year and enrolls for their third, they are exponentially more likely to graduate from that same institution. In other words, a student is much more likely to leave the institution in their first two years than any other year on campus. JMU would benefit from creating a system that is suited for at least the first two years, but no evidence to our knowledge exists of the harms of having an early-alert system be used for students who are past their second year.

*Table 3. Number of students who left JMU by number of semesters and years attended*

| Year | Semester | # who left JMU |
|---|---|---|
| 1 | 1 | 664 |
| | 2 | 380 |
| 2 | 3 | 353 |
| | 4 | 186 |

| Year | Semester | # who left JMU |
|---|---|---|
| 3 | 5 | 183 |
| | 6 | 68 |
| 4 | 7 | 45 |
| | 8 | 17 |
| Total | | 1896 |

### Question 3: Why do students leave JMU?

Students leave higher education for a variety of reasons. At JMU, it is no different. Data on the reason students leave is taken from student records. In the process, students either select a primary reason for leaving, or a reason is assigned to them upon meeting with the proper offices. Tables 4-6 break down those reasons by select racial/ethnic and gender identities, as well as first-generation status. Overall, the top students leave are due to psychological reasons, transferring to a different institution, taking a leave of absence, and feeling a lack of fit and/or sense of belonging on campus. Not many students are marking academics or their major as the reason for leaving JMU, meaning that things like GPA and coursework may be less relevant to retention on campus.

*Table 4. Count of Reasons Students Leave JMU by Racial/Ethnic Identity*

| Reason | Race | | | | | Total |
|---|---|---|---|---|---|---|
| | Asian | Black | Hispanic/Latinx | Multiracial | White | |
| Academic | 0 | 3 | 1 | 5 | 39 | 48 |
| COVID-19 | 2 | 4 | 1 | 9 | 74 | 90 |
| Extenuating Circumstances | 0 | 0 | 2 | 2 | 7 | 11 |
| Family | 8 | 1 | 3 | 12 | 42 | 66 |
| Finances | 10 | 10 | 1 | 14 | 84 | 119 |
| Fit/Sense of Belonging | 8 | 10 | 2 | 20 | 127 | 167 |
| Home | 6 | 1 | 0 | 12 | 61 | 80 |
| Health | 3 | 10 | 0 | 18 | 160 | 191 |
| Job | 4 | 1 | 0 | 6 | 28 | 39 |
| Leave of Absence | 10 | 9 | 3 | 23 | 152 | 197 |
| Major | 2 | 3 | 3 | 3 | 18 | 29 |
| Medical | 1 | 3 | 1 | 6 | 47 | 58 |
| Personal | 3 | 11 | 5 | 17 | 97 | 133 |
| Psychological | 9 | 8 | 5 | 26 | 216 | 264 |
| Transfer | 13 | 11 | 4 | 28 | 188 | 244 |
| Total | 79 | 85 | 31 | 201 | 1340 | 1736 |

The top reasons Asian students leave campus are lack of financial security, transferring to a different institution, and taking a leave of absence. Black students note they are leaving JMU most prevalently because of finances, personal reasons, health concerns, and a lack of fit/sense of belonging. Hispanic/Latinx students are noting personal reasons and transferring as reasons to leave JMU. Finally, white students are leaving JMU primarily because of psychological reasons and transferring to another institution, but are also leaving due to health concerns and lack of fit/sense of belonging. All groups note that psychological/mental health is a prevalent reason for leaving JMU, while no group has a large proportion that notes academics as the primary reason for leaving.

*Table 5. Count of Reasons Students Leave JMU by Gender*

| Reason | Gender | | Total |
|---|---|---|---|
| | Female | Male | |
| Academic | 20 | 32 | 52 |
| COVID-19 | 54 | 40 | 94 |
| Extenuating Circumstances | 4 | 10 | 14 |
| Family | 38 | 32 | 70 |
| Finances | 75 | 52 | 127 |
| Fit/Sense of Belonging | 115 | 55 | 170 |
| Home | 62 | 18 | 80 |
| Health | 122 | 75 | 197 |
| Job | 9 | 30 | 39 |
| Leave of Absence | 101 | 107 | 208 |
| Major | 18 | 13 | 31 |
| Medical | 34 | 25 | 59 |
| Personal | 56 | 87 | 143 |
| Psychological | 141 | 128 | 269 |
| Transfer | 167 | 85 | 252 |
| Total | 1016 | 789 | 1805 |

Female students have left JMU mostly to transfer to another institution, but have also noted psychological health, lack of fit/sense of belonging, and choosing to take a leave of absence as reasons. Male students are slightly similar; they note transferring, psychological reasons, personal reasons, and taking a leave of absence as primary reasons for leaving JMU. Both groups note transferring and psychological reasons as top reasons for leaving JMU.

*Table 6. Count of Reasons Students Leave JMU by First-Generation Status*

| Reason | Continuing- Generation | First-Generation | Total |
|---|---|---|---|
| Academic | 40 | 5 | 45 |
| COVID-19 | 71 | 13 | 94 |
| Extenuating Circumstances | 7 | 3 | 10 |
| Family | 35 | 16 | 51 |
| Finances | 79 | 23 | 102 |
| Fit/Sense of Belonging | 140 | 18 | 158 |
| Home | 71 | 11 | 82 |
| Health | 146 | 30 | 176 |
| Job | 24 | 4 | 28 |
| Leave of Absence | 153 | 24 | 177 |
| Major | 24 | 4 | 28 |
| Medical | 54 | 4 | 58 |
| Personal | 99 | 17 | 116 |
| Psychological | 231 | 27 | 258 |
| Transfer | 194 | 44 | 238 |
| Total | 1368 | 243 | 1611 |

Students who have at least one guardian with a college degree (continuing-generation students) note psychological concerns, transferring, taking a leave of absence, health concerns, and lack of belonging as the top reasons for leaving JMU. First-generation students list transferring, psychological reasons, health concerns, taking a leave of absence, and finances as the top reasons for leaving JMU. Both groups leave most often for psychological reasons, transferring, taking a leave of absence, and health concerns.

Together, Tables 4-6 show:

1. Mental health is a top concern for all students, regardless of identity.
2. Marginalized students are more affected (proportionally) by finances and sense of belonging than privileged students.
3. Academics are rarely a point of worry for students who choose to leave JMU.

Although these two points are significant to note, more research should be done on the student population to find points in students' experiences that lead them to have mental health concerns or feel a lack of sense of belonging. Knowing students' experiences from their point of view will help the QEP group better understand the need for and implementation of an early alert system.

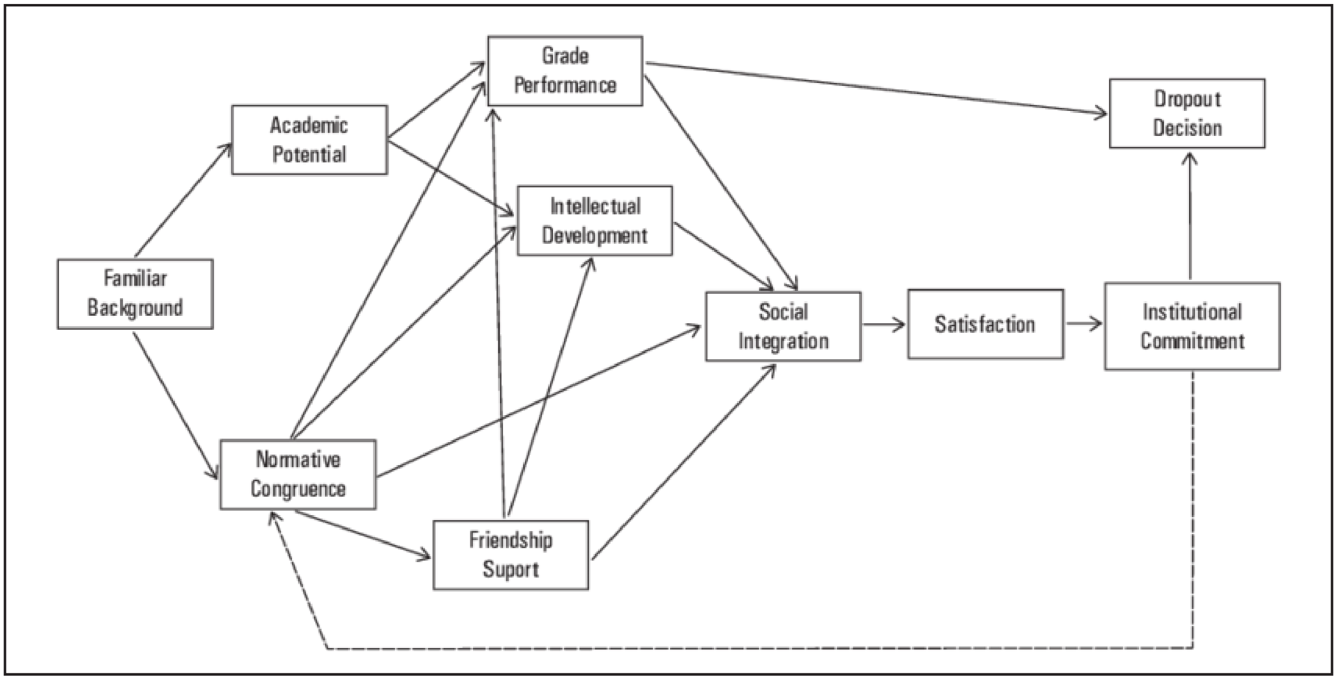
### *Conclusion*

Although relatively not many students leave James Madison University, there is insight to be gained on when and why students leave JMU. Overall, psychological reasons lead the most students to leave JMU every year, yet there are other concerning reasons. Many marginalized students leave JMU for reasons that can be linked to their identity, such as a lack of connection to campus and financial concerns. Given that noncognitive factors like the ones listed can lead to poor academic performance, we must find a way to target students when they first show struggle in noncognitive factors on campus. In order to know when and how to intervene, we must know what factors are important to student success according to research and evidence gathered at JMU.

# Section II: Research on Undergraduate Retention

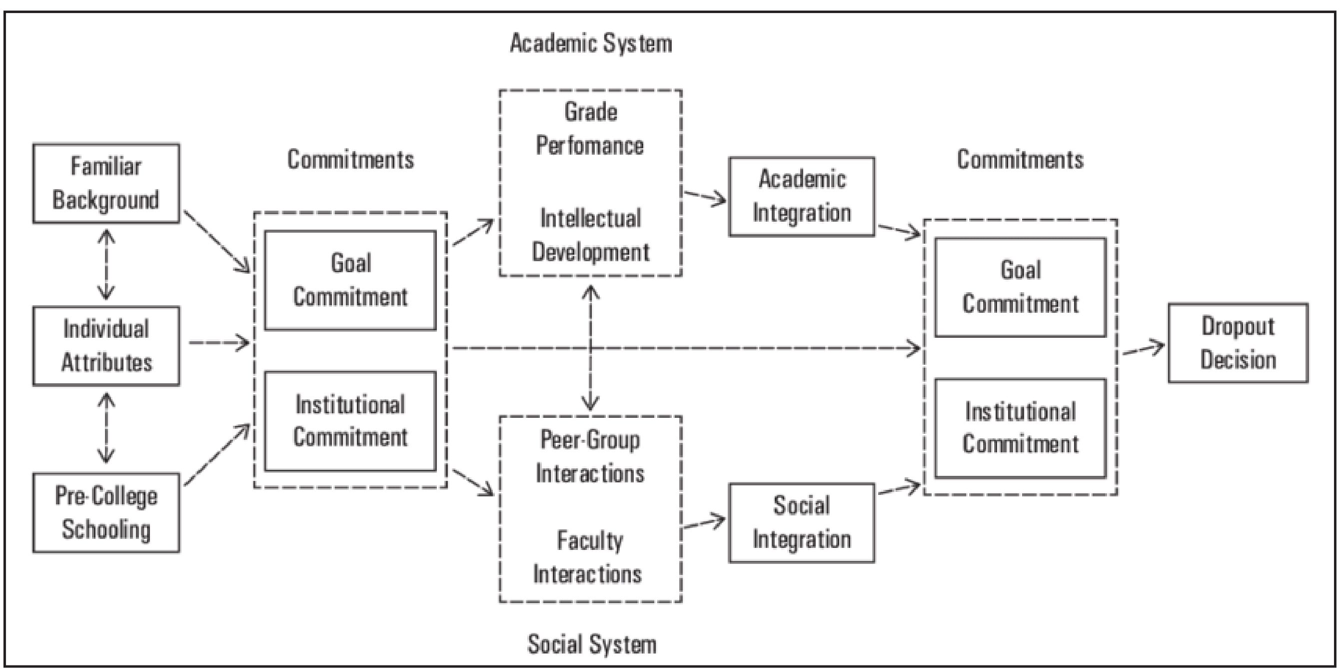
In order to know what to look for to ensure accurate intervention, we looked to literature to understand the ways students interact with their institution, and how those interactions affect a student's decision to stay or leave the university. Here, we present the three competing student retention models in literature.

*Model 1—The Undergraduate Dropout Process Model (Spady,1980; 1981)*




The undergraduate dropout process model is one of the first models that described how students navigated college. This model assumes that a decision to leave campus depends on 1) grades and intellectual development, 2) quality of friendships, and 3) a student's norms blending in with campus. As this model was the first of it's kind, there are more universal designs more commonly used in today's research; this model is older and does not generalize to the campus experience today.

*Model 2— The Institutional Departure Model (Tinto, 1975;1993)*



Tinto's institutional departure model is the most widely applied and used model in higher education retention research, due to its integration of multiple disciplines and interpretability. Tinto argued that students' experiences, primarily in the first year of college, are dependent upon their ability to disassociate from their old communities (e.g., high school community) and integrate into their new community (i.e., their college community). During integration, the student must navigate both their social and academic systems. Their interactions with these systems, primarily interactions with faculty and peers, will inform a student's intentions on whether to stay at the university. This model is widely used in higher education, and validity studies have shown this model's generalizability. The primary disadvantage to this model is that there is no consistent way to measure the constructs defined in this model.

*Model 3 (Championed Model)- The Meta-Analytic Structural Equation Model for Persistence (Dolan, 2019)*

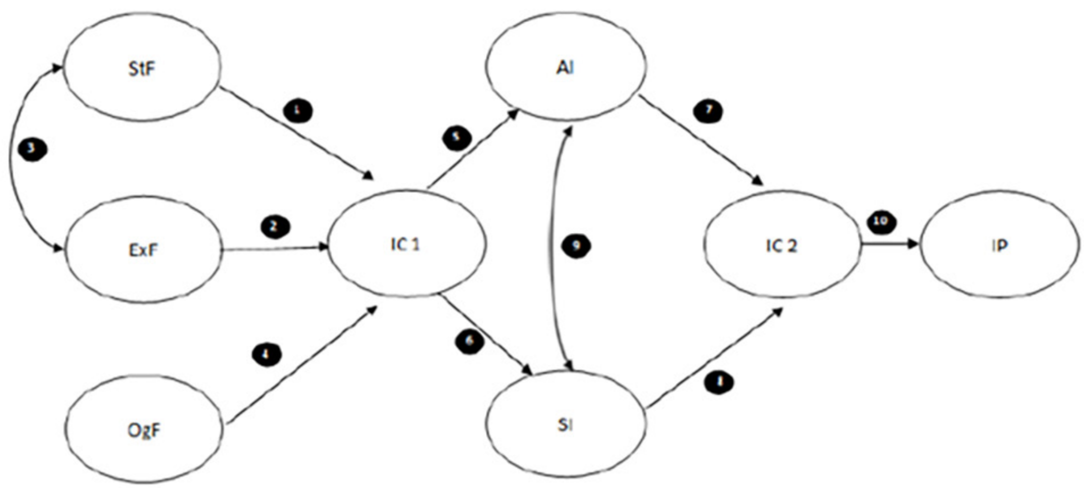



*Figure 1.* Proposed MASEM model. (Repeated here for ease of reference.)

StF: Student factors, ExF: External factors, OgF: Organizational factors, IC1: 1st measure of institutional commitment, SI: social integration, AI: Academic Integration, IC2: 2nd measure of institutional commitment, IP: Intent to persist

Dolan's meta-analytic model is the newest retention model that combines previous models (including Tinto and Spady) to create a comprehensive model to represent the student experience. This meta-analytic model defines each factor via observed variables, and each observed variable has a measure associated with it. We have chosen to champion this model because of how well-defined each factor is.

Through our championed model (model 3), we gained insight on what things are important for students to know, think, or do in order to raise their intentions to stay at JMU. Instead of creating a statistical model with all of these variables and factors to predict retention at JMU, we first looked through literature to determine what groups may have preexisting differential rates in retention, given the context of JMU: A large, southeastern R2 primarily white institution located between multiple metropolitan areas.

After scanning literature, the initial statistical models to assess naturally occurring differences in retention rates are:

| First-Order | Second-Order | Third-Order |
|---|---|---|
| Race | Race*Gender | Race*Gender*SES |
| Gender | Race*Socioeconomic Status | Race*Gender*First-Generation Status |
| Socioeconomic Status | Race*First Generation Status | |
| First-Generation Status | Gender*Socioeconomic Status | |
| | Gender*First-Generation Status | |
| | SES*First-Generation Status | |

Logistic Regression will be used to model the likelihood of retention past the first year on these variables. Nested model testing will be used to find the most parsimonious model that explains the most variance in retention rate after the first year of college. After the best statistical model is found, we will then add in ISSAQ factor scores as covariates to determine the best way to predict retention in the JMU body, based on social identities and ISSAQ scores.

# Appendix E: ISSAQ Validity Presentation

## ISSAQ Predictive Validity:
*James Madison University*

ROSS MARKLE, PH.D.

DIA
Higher Education Collaborators

1

## Data Collection Overview

1. 5022 total ISSAQ responses were gathered as part of Orientation during Summer 2021
2. 4300 responses matched to JMU outcomes data, with 4,163 providing valid responses (e.g., full data, sufficient response time, non-duplicate records)
   a. Sample sizes for ACT score differ from ISSAQ data (*n* = 574)
3. Outcomes included
   a. DFW's in first semester
   b. First-semester GPA
   c. First-year GPA
   d. Retention to second year

DIA
Higher Education Collaborators

2


DIA
Higher Education Collaborators



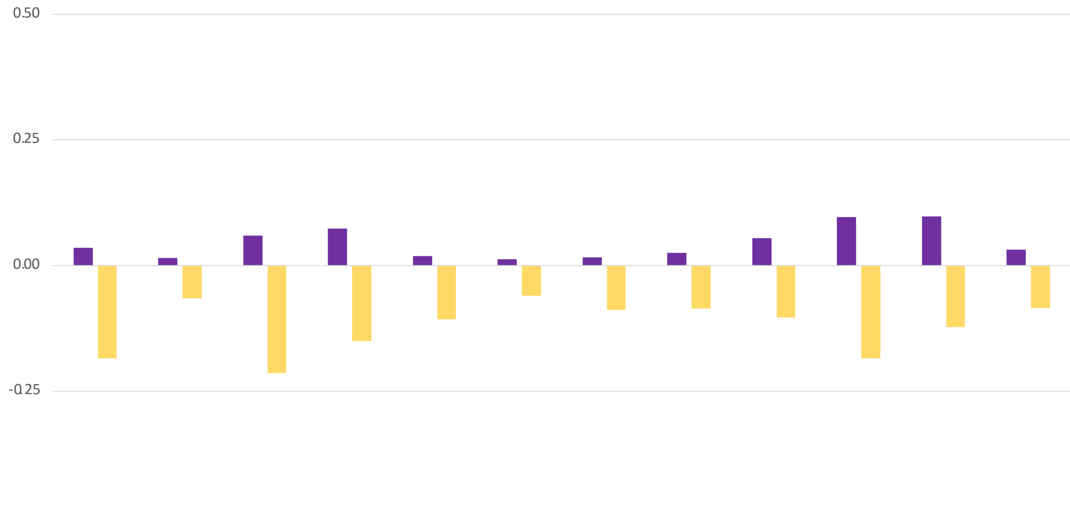
# ISSAQ Scoring

**Item Scoring**:
- Create quantitative values for agree/disagree statements (i.e., 1 to 4)
- Adjust any negatively worded or reverse-scored items

**Raw Scoring:**
- Mean of all responses aligned to a particular construct

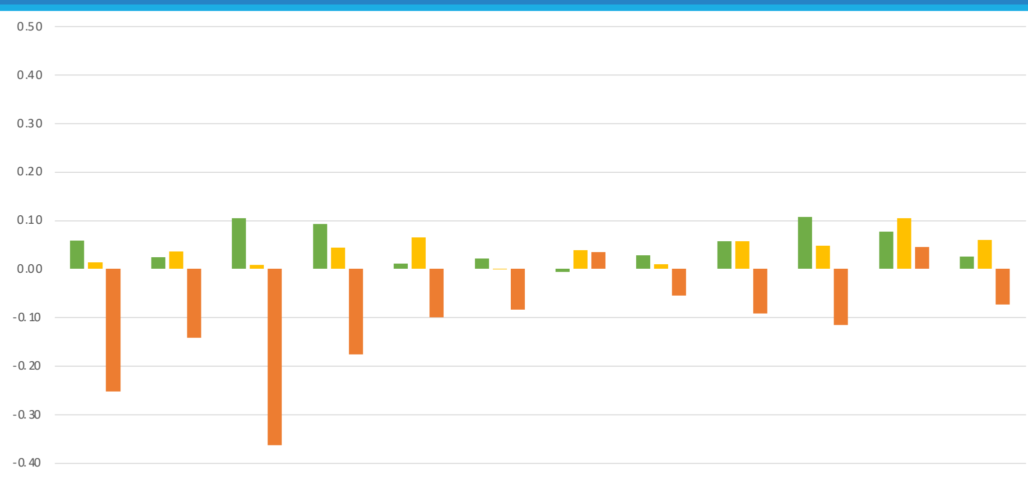
**Scale Scoring**:
- Using large, normative sample, adjust every factor to Z-score distribution (M=0, SD=1)

DIA
Higher Education Collaborators




| | Organization | Quality Focus | Engagement | Goal Commitment | Persistence | Effort Focus | Calmness | Coping Strategies | Self-Efficacy | Sense of Belonging | Institutional Commitment | Help Seeking |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Retain (n=3791) | 0.03 | 0.02 | 0.06 | 0.07 | 0.02 | 0.01 | 0.02 | 0.03 | 0.06 | 0.10 | 0.10 | 0.03 |
| Attrit (n=372) | -0.18 | -0.07 | -0.21 | -0.15 | -0.11 | -0.06 | -0.09 | -0.08 | -0.10 | -0.18 | -0.12 | -0.08 |

5




| | Organization | Quality Focus | Engagement | Goal Commitment | Persistence | Effort Focus | Calmness | Coping Strategies | Self-Efficacy | Sense of Belonging | Institutional Commitment | Help Seeking |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| No DFWs (n=2,945) | 0.06 | 0.02 | 0.11 | 0.09 | 0.01 | 0.02 | -0.01 | 0.03 | 0.06 | 0.11 | 0.08 | 0.03 |
| Only 1 DFW (n=748) | 0.01 | 0.04 | 0.01 | 0.04 | 0.07 | 0.00 | 0.04 | 0.01 | 0.06 | 0.05 | 0.10 | 0.06 |
| 2 or more DFW's (n=470) | -0.25 | -0.14 | -0.36 | -0.18 | -0.10 | -0.08 | 0.04 | -0.05 | -0.09 | -0.12 | 0.05 | -0.07 |

6

| Criterion Correlations | 1st Term GPA | 1st Year GPA |
|---|---|---|
| ACT* | **.25** | **.26** |
| Organization | *.15* | *.16* |
| Quality Focus | .08 | *.10* |
| Engagement | **.20** | **.22** |
| Goal Commitment | *.13* | *.14* |
| Persistence | .05 | .05 |
| Effort Focus | .02 | .02 |
| Calmness | -.02 | -.03 |
| Coping Strategies | .04 | .04 |
| Self-Efficacy | .07 | .07 |
| Sense of Belonging | .07 | .07 |
| Institutional Commitment | .00 | .01 |
| Help Seeking | .04 | .05 |

7

## Effect Sizes (Cohen's *d*) Across DFW Groups

*d's < .10 not listed (not practically significant

**Sample sizes for ACT score differ from ISSAQ data ($n$ = 434, 87, 53 for 0, 1, and 2 DFW's, respectively)

| Factor | Comparing Retain vs. Attrit | Comparing 0 DFW's to 1 DFW | Comparing 0 DFW's to 2+ DFW's |
|---|---|---|---|
| ACT | | .41 | .30 |
| Organization | .22 | | **.31** |
| Quality Focus | | | .17 |
| Engagement | .28 | .10 | **.48** |
| Goal Commitment | .24 | | **.28** |
| Persistence | .13 | | .11 |
| Effort Focus | | | .11 |
| Calmness | .10 | | |
| Coping Strategies | .11 | | |
| Self-Efficacy | .16 | | .15 |
| Sense of Belonging | .29 | | **.23** |
| Institutional Commitment | .23 | | |
| Help Seeking | .12 | | .10 |

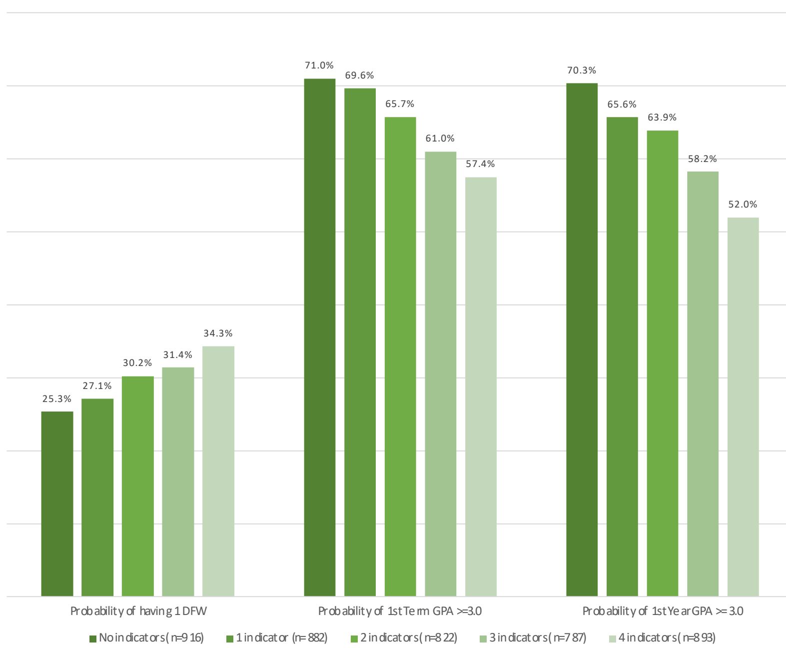
8

# Data in Action

Created a JMU-specific academic success index based on four largest indicators of DFW (Cohen's *d*)

If student scored "opportunity" in one of those areas, added one to success index

This graphic shows the various outcomes across 5 possible levels of that index




9

# Next Steps

Possible uses:

- How do we use assessment data to proactively identify students and provide support early on?
- What student support areas would be involved?

"Research" questions:

- How does the predictive efficacy of ISSAQ relate to academic factors?
  - Need to consider practical issues of data, as we'd be gathering academic information from ISSAQ and not institutional records.
  - Unfortunately, as these data were gathered during the pilot, questions about ACT/SAT/HSGPA were not included.
- How do these findings generalize across groups? (E.g., gender, race/ethnicity, major, involvement with certain programs)

DIA
Higher Education Collaborators

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# Appendix F: Literature Review Subgroup Annotated Bibliography

In working through extensive literature about data mining, learning analytics, student success outreach, and equity in higher education outcomes, the research literature subcommittee of the QEP Working Group found ourselves returning again and again to three critical areas of the early alert design process—values and ethics, learning analytics and big data, and responses and interventions in support of equitable outcomes—which we focused on for three micro-reports written by members of our team.

However, many of the articles that covered topics outside of the themes of those three micro-reports still contained information that could be incredibly relevant to the working group's efforts moving forward. We decided to capture these "everything else" resources in an annotated bibliography. Many of the articles we reviewed covered topics that were not covered by our micro-reports, yet could be relevant to our work moving forward. We captured these "everything else" resources in this annotated bibliography. It is far from perfect (including inconsistencies in its attributions of paraphrases and quotations), so please don't view it as an official document. But hopefully it captures useful information that can be easily scanned for applicability by various working teams moving forward.

All articles have been loaded into a free, easy-to-use, online platform called Zotero. Please ask Jolie Lewis (lewis3jl@jmu.edu) to be added to the group's Zotero library if you would like access to these articles. We also invite colleagues to add to this document as you encounter other resources that may assist with our collective work.

## Predictive Analytics: Overarching Resources

*Lester, Jaime, et al. "Learning Analytics in Higher Education." ASHE Higher Education Report, vol. 43, no. 5, 2017, p. 143.*

This 140+ page report from the Association for the Study of Higher Education (ASHE) takes a deep diver into learning analytics, with chapters introducing current trends and research; exploring organizational context and capacity in terms of decision-making, capacity, readiness, and adoption; the role of faculty, advisors and students in decision-making; ethical and privacy considerations; and recommendations moving forward.

*Barshay and Aslanian. "Predictive Analytics Are Boosting College Graduation Rates, but Do They Also Invade Privacy and Reinforce Racial Inequities?" The Hechinger Report, 6 Aug. 2019, http://hechingerreport.org/predictive-analytics-boosting-college-graduation-rates-also-invade-privacy-and-reinforce-racial-inequities/.*

This article, published in the Hechinger Report as a collaboration with American Public Media, introduces predictive analytics that could be understood by most audiences, capturing in broad brush strokes some of the central issues around colleges using big data. The article includes a case study / deeper dive into the use of predictive analytics at Georgia State, an early contract partner with EAB. The article discusses the history of how predictive analytics came to be used in higher education, highlights positive outcomes in terms of students staying in college and graduating, and provides an overview of concerns, including a lack of transparency with students and concerns that the reliance of predictive analytics on past experiences that could be the result of bias could perpetuate those biases.

*Selwyn, Neil. "What's the Problem with Learning Analytics?" Journal of Learning Analytics, vol. 6, no. 3, Dec. 2019, pp. 11–19, https://doi.org/10.18608/jla.2019.63.3.*

From The Journal of Learning Analytics comes a helpful analysis of concerns around the usage of learning analytics. Selway, a scholar outside the field, argues a sociotechnical approach in examining and engaging in critical dialogue about learning analytics. He identifies a series of potential negative consequences in implementing learning analytics: a reduced understanding of education, ignoring broader social contexts, reducing student and teacher capacity for decision-making, using analytics as a tool for surveillance rather than support, disadvantaging large numbers of people, serving institutional rather than individual interests, and creating opportunities for institutions to be performative instead of transformative. He also raises concerns about some of the values of learning analytics: an oversized faith in data, techno-idealism, limitations put on individual choice and agency and an exploitative data economy. He makes suggestions for how to rethink the design, economics, and governance of learning analytics, and how to increase public understanding of the field and its tools.

## Preparing for & Enacting Institutional Change

### Institutional Readiness for Change

*Arnold, Kimberly, et al. "An Exercise in Institutional Reflection: The Learning Analytics Readiness Instrument (LARI)." ResearchGate, 2014, https://doi.org/10.1145/2567574.2567621.*

Co-authors from the University of Wisconsin-Madison, the University of Michigan, and Purdue University describe the instrument they developed to help institutions prepare for a successful analytics implementation. There are 90 items in the instrument pertaining to: 1) ability, 2) data, 3) culture and process, 4) governance and infrastructure, and 5) overall readiness perception.

### Approaches to Enacting Institutional Change

*Ishimaru, Ann M., and Mollie K. Galloway. "Hearts and Minds First: Institutional Logics in Pursuit of Educational Equity." Educational Administration Quarterly, vol. 57, no. 3, Aug. 2021, pp. 470–502, https://doi.org/10.1177/0013161X20947459.*

In studying two school equity teams in a K-12 context over the period of a year, Ishimaru and Galloway found that despite "differences between principals, the trajectories of team conversations, and school and district contexts," both teams ultimately decided to address people's beliefs and mindsets about equity before trying to enact other kinds of institutional change (472). The researchers suggested that this approach—a "theory of change" that prioritizes the winning over of "hearts and minds" first—may limit an organization's ability to enact actual change. They recommend other approaches that still prioritize the importance of dialogue: "addressing beliefs and practice in tandem, or changing practice first, then shifting educator beliefs and expectations on realizing improved student learning" (494).

*Kinzie, Jillian, and George Kuh. "Reframing Student Success in College: Advancing Know-What and Know-How." Change: The Magazine of Higher Learning, vol. 49, no. 3, May 2017, pp. 19–27, https://doi.org/10.1080/00091383.2017.1321429.*

"The student success agenda must be guided by a conceptual structure emphasizing how student success will be achieved," write Kinzie and Kuh (20). There is a tremendous volume of literature that examines what tools and practices can improve college access and student success and help to address achievement gaps, yet institutions struggle to implement "the kinds of promising policies and practices that work elsewhere." Or they do so in ways that lack focus and connection, or are inappropriate for their institution and student body, which can lead to "initiative fatigue" (22). They recommend ending the buffet approach to student success and instead creating driver diagrams to define a theory of change defining at least three levels of a "proposed solution path": the description of the goal or desired outcome, the conditions that are needed to achieve that goal (primary drivers), and the specific activities that create those conditions (secondary drivers) (23). Examples and further resources are included.

*Klempin, Serena, and Melinda Mechur Karp. "Leadership for Transformative Change: Lessons from Technology-Mediated Reform in Broad-Access Colleges." The Journal of Higher Education, vol. 89, no. 1, Jan. 2018, pp. 81–105, https://doi.org/10.1080/00221546.2017.1341754.*

Klempin and Karp looked at case studies of iPass efforts at six different colleges to answer two questions: "(a) What do colleges' early implementation plans and experiences reveal about the potential for technology adoption to drive transformative change? And (b) how do different approaches to college leadership influence technology adoption and transformative change?" They focused on the interrelated nature of addressing system, process, and attitudinal change simultaneously, as all three are required for a successful outcome. They found that multi-level leadership—both from upper-level administrative leadership and midlevel project managers—committed to shared goals and change was necessary to transformative change. They define adaptive (vision for change) vs. technical leadership (logistics-focused) styles, and then categorized the institutions in their study by determining which leadership style was demonstrated by the institution's administration, and which was demonstrated by midlevel project managers. Ultimately, they said, "the only colleges making significant changes to structures, processes, and attitudes were the sites where institutional and project leaders shared a clear vision for adaptive change." They viewed iPass as a complex reform, and they made sure to communicate how it would impact the daily work of advisors. Sites with other leadership pairings did not experience transformative change.

*Fuad, Khaleed, et al. Student Success through Digital Innovation: A Change Model. Research Report, Center for Digital Innovation | J Mack Robinson College of Business | Georgia State University, 2021, p. 6, https://theuia.org/sites/default/files/2021-07/GSU-Research-Report.pdf.*

Three researchers took a deep dive—through interviews with key faculty and staff and review of archival data—into initiatives focused on digital innovation at Georgia State University to answer the question: "How does a higher education institution effectively manage change through digital innovations for student success?" They identified three areas of digital innovation to support student success: 1) teaching and learning (LMS, adaptive online math learning), 2) monitoring and advising (EAB's GPS, 60 academic advisors to monitor and respond to alerts), and 3) engaging and informing students (Pounce AI chatbot). How were they able to enact these changes? "Along the dimensions of context, content, and process of change, GSU took important steps to rationalize, initiate, and administer" (3). The context component required strong and visionary leadership at the highest levels of administration combined with an unwavering commitment to student success among faculty and staff and outsourcing for technological expertise. The process component benefited from a "culture of collaborative and participatory innovation and learning," evidence-based solutions to problems, and starting small and then scaling (4). Both led to the content of the change: intentionally focusing on support along the student journey, engaging predictive analytics and advising systems to respond to needs, and recognizing the importance of faculty and staff in making the new technologies work.

## Situating Early Alert within a Multi-dimensional, Institutional Approach to Justice, Equity, Diversity, and Inclusion

### Institutional Policy Needed in Support of Student Success

*Erwin, Ben, and Jennifer Thomsen. Addressing Inequities in Higher Education. Policy Guide, Education Commission of the States, July 2021, p. 14, https://www.ecs.org/wp-content/uploads/Addressing-Inequities-in-Higher-Education.pdf.*

This 14-page policy guide from the Education Commission from the States identifies areas for policy review around 1) college readiness supported through K-12 education systems, 2) student transitions from high school to college, including how underprepared students are served by developmental education upon arrival, and 3) how institutions provide support to students in degree attainment. In the third area, they share questions to consider related to retention and completion related to evaluating and addressing campus climate, offering culturally relevant courses and instruction, recruiting and retaining diverse faculty, offering supports specifically for students of color, providing meaningful academic advising, and targeting financial aid to support retention. They share policy advice related to student debt, as student loan debt falls disproportionately on Black students. This report does not include in-depth early-alert research but is an important reminder to contextualize our efforts within a broader array of equity-focused initiatives at the university. It also encourages us to keep in mind students' financial stressors in early-alert planning.

### Completion Outcomes Are Impacted by Representation

*Bowman, Nicholas A., and Nida Denson. "Institutional Racial Representation and Equity Gaps in College Graduation." The Journal of Higher Education, vol. 0, no. 0, Sept. 2021, pp. 1–25, https://doi.org/10.1080/00221546.2021.1971487.*

Researchers found that universities where there was same-race representation as well as representation of other minoritized groups among both the student body and instructors see more racial equity in graduate outcomes. "[In] fact, no Black-White and Latinx-White gaps were present when Black or Latinx students, respectively, comprised at least half of undergraduates at that institution" (1). These patterns were seen primarily at institutions where there were few online students, suggesting that in-person interactions "facilitate situational racial cues and interpersonal experiences that may foster success for racially minoritized students" (1).

### Fairness and Institutional Communication to Students May Impact Persistence

*Dolan, Amanda. Synthesizing Undergraduate College Student Persistence: A Meta-Analytic Structural Equation Model. Kent State University College of Education, May 2019.*

This 173-page dissertation offers a meta-analysis of many research studies and proposes a 10-part model in which a student's background characteristics (including GPA, demographics, etc.) and outside commitments (which influence each other) combine with organizational factors (size, culture, sense of belonging, fairness of policies, communication to students, and satisfaction with the college, p. 51) to determine the student's initial commitment to the institution. Their commitment then drives their academic and social engagement (which influence each other), which then leads to their institutional commitment at the end of their first semester, which in turn drives their intent to persist into a second semester. Of the 10 paths proposed for the model, all were found to be statistically significant except student characteristics (it was the weakest correlation in the analysis, even though high school GPA is typically found to be directly related to persistence-p. 99, 110) and external factors. The impact of organizational factors on commitment, interestingly, was significant. Read sections starting around page 112 for details about the various pathways in the model that did show significance. How can JMU's early alert work support "sense of belonging" in students and promote fair policies and better communication to students across the institution?

### The Importance of Collecting and Connecting Comprehensive, Disaggregated Data

*Wong, Nancy. "Data for Equity: Closing Racial and Economic Gaps Through a Federal-State Partnership." The Institute for College Access & Success, July 2021, https://ticas.org/affordability-2/student-aid/federal-state-partnerships/data-for-equity-closing-racial-and-economic-gaps-through-a-federal-state-partnership/.*

While this July 2021 paper from the Institute for College Access and Success focuses on the need for greater data collection and analysis related to educational success and outcomes at the state level—with a nod to the College Transparency Act which has passed the U.S. House of Representatives and been referred to committee in the U.S. Senate—the points made can be applied to some degree at the institutional and even programmatic level. The article points out that systemic barriers not only make it more difficult for BIPOC students and students from low-income backgrounds to earn a degree, but also to receive a comparable return on their investment. The paper makes a case for data transparency, data coverage, and data connection, arguing that data points should include costs, financial aid, access, enrollment, and completion—a broader scope of data than have been historically considered—and should include data points for all students that can be fully disaggregated by race, income, first-generation student status, veteran status, and gender, as well as combinations of those categories.

### Increasing Accuracy and Transparency in Predictive Models

*Bertolini, Roberto, et al. "Enhancing Data Pipelines for Forecasting Student Performance: Integrating Feature Selection with Cross-Validation." International Journal of Educational Technology in Higher Education, vol. 18, no. 1, Aug. 2021, p. 44, https://doi.org/10.1186/s41239-021-00279-6.*

A 23-page article from the International Journal of Educational Technology in Higher Education takes on three research questions related to simplifying the data pipeline used in data mining methods (DMM), identifying whether using filter feature selection techniques in developing algorithms predicting student success could improve accuracy (as well as transparency), and identifying the sets of student attributes, both academic and nonacademic, that contribute to student performance in a gateway biology course. They found that using pre-processing filter techniques instead of analyzing all available features could be successful in developing "more robust and less convoluted educational data science pipelines," while also allowing the "black-box" algorithms to be more easily explained to stakeholders. They also found that academic and course features were more predictive of student success than other academic factors (LMS usage was less predictive than they expected, but they noted that there may have been explanations for that). Finally, they talked briefly about the importance of evaluating algorithms for stability. Please note: this article includes an analysis of data mining methods that goes well beyond my level of expertise but could be very useful to a team looking at design related to educational data mining for the QEP.

*Bird, Kelli A., et al. "Bringing Transparency to Predictive Analytics: A Systematic Comparison of Predictive Modeling Methods in Higher Education." AERA Open, vol. 7, Jan. 2021, p. 23328584211037630, https://doi.org/10.1177/23328584211037630.*

This source begins by talking about the importance of accuracy, stability and fairness in predictive analytics—but college administrators have little to no ability to evaluate predictive analytics software on these dimensions due to the proprietary nature of the algorithms, which leads to risks for both institutions and students through misidentification and bias reinforcement. The study compares two dimensions of predictive modeling: different approaches to sample and variable construction and different modeling approaches (tree-based vs. Regression-based). Some important findings (15): 1. "the notion of 'risk' is not stable and can vary meaningfully across the modeling strategy used," and 2. "institutions would realize important gains in model accuracy through a thoughtful sample and predictor construction" (sophisticated tree-based models perform more accurately than simpler regression-based models, but the gains in accuracy are small). They suggest that using a sophisticated model could be important if an institution has limited choice over modeling decisions (due to data limitations, legal restrictions on inclusion of student attributes, etc.), but that when colleges can only target a small subset of students for additional support, regression models have an advantage. They also note other important considerations beyond accuracy: bias reinforcement, ethical questions around using certain data (such as dorm swipes), the need to consider benefits vs. costs when predictive modeling can be so expensive, and the importance of not conflating accuracy in a predictive model with designing appropriate and effective intervention. A good model in and of itself doesn't impact student outcomes. Note that two of the authors hail from University of Virginia: Kelli A. Bird and Benjamin L. Castleman.

## Promoting Agency: The Role of Faculty, Advisors, and Students in LA Design & Intervention

Engaging Students

*Buckingham Shum, Simon, et al. "Human-Centred Learning Analytics." Journal of Learning Analytics, vol. 6, no. 2, July 2019, pp. 1–9, https://doi.org/10.18608/jla.2019.62.1.*

In 2019, the Journal of Learning Analytics published a special section of five papers about "Human-Centered Learning Analytics," which they define thus: "The essence of adopting a human-centered approach is that meanings, interaction opportunities, functions, and attributes associated with the system should be defined by the people for whom the system is intended, rather than imposed by designers or researchers" (2). Whereas LA was around 10 years old at that time, the introduction describes HCLA as being in its toddlerhood. In addition to the included articles, the section points toward other resources in HCLA.

### Engaging Advisors and Faculty

*Scheers, Hanne, and Tinne De Laet. "Interactive and Explainable Advising Dashboard Opens the Black Box of Student Success Prediction." Technology-Enhanced Learning for a Free, Safe, and Sustainable World, edited by Tinne De Laet et al., Springer International Publishing, 2021, pp. 52–66, https://doi.org/10.1007/978-3-030-86436-1_5.*

Advisors and students aren't likely to trust models--especially black-box models--when they can't test the algorithms against their own beliefs about the reasonableness of the model. This article user-tests a couple of explainable AI (XAI) models that predict student success based on indicators prior to and/or as they arrive at college: number of hours of math courses in high school, time management skills, etc. The visualizations were presented in such a way that students could see where they were strong and weak--but also what areas they could yet impact, and what might happen to their likelihood of success if they could improve those areas, such as managing anxiety, improving test strategies, etc. Helpful for thinking about implementation--who and how would respond to data from predictive models?

*Jones, Kyle M. L. "Advising the Whole Student: EAdvising Analytics and the Contextual Suppression of Advisor Values." Education and Information Technologies, vol. 24, no. 1, Jan. 2019, pp. 437–58, https://doi.org/10.1007/s10639-018-9781-8.*

From the abstract: This study shares findings from interviews with professional advisors at a public university regarding the recent adoption of eAdvising technologies with prescriptive and predictive features. The advisors "rejected the tools due to usability concerns, moral discomfort, and a belief that using predictive measures violated a professional ethical principle to develop a comprehensive understanding of their advisees."

*Klein, Carrie, et al. "Learning Analytics Tools in Higher Education: Adoption at the Intersection of Institutional Commitment and Individual Action." The Review of Higher Education, vol. 42, no. 2, 2019, pp. 565–93, https://doi.org/10.1353/rhe.2019.0007.*

From the abstract: This case study at a large, public research university sought to understand organizational barriers, incentives and opportunities in faculty (6) and professional advising staff (21) adopting learning analytics tools. "Organizational context and commitment, including structures, policies, processes, and leadership impact individual decisions to trust and adopt learning analytics tools." The abstract also stresses the importance of communication about the implementation plan, which needs to be clear, thorough, and inclusive.

*Delmas, Peggy M., and Tracey N. Childs. "Increasing Faculty Engagement in the Early Alert Process." Innovations in Education and Teaching International, vol. 58, no. 3, May 2021, pp. 283–93, https://doi.org/10.1080/14703297.2020.1740102.*

JMU's Madison CARES program already provides an opportunity for university faculty and staff to provide alerts when they are concerned about students. Based on its abstract, this article talks about the importance of the faculty role in providing early alerts, identifies practices to encourage faculty usage of an EAS, such as communicating ease of use and positive outcomes.

*Pistilli, Matthew D., and Gregory L. Heileman. "Guiding Early and Often: Using Curricular and Learning Analytics to Shape Teaching, Learning, and Student Success in Gateway Courses." New Directions for Higher Education, vol. 2017, no. 180, 2017, pp. 21–30, https://doi.org/10.1002/he.20258.*

Abstract: "This chapter provides information on how the promise of analytics can be realized in gateway courses through a combination of good data science and the thoughtful application of outcomes to teaching and learning improvement efforts—especially with and among instructors."

## Ethical Considerations in Learning Analytics

*Ferguson, Rebecca. "Ethical Challenges for Learning Analytics." Journal of Learning Analytics, vol. 6, no. 3, Dec. 2019, pp. 25–30, https://doi.org/10.18608/jla.2019.63.5.*

This article is part of a dialogue about the ethical challenges of learning analytics, and engages with the six broad areas of ethical challenges identified for the field in 2016: duty to act, informed consent, safeguarding, equality and justice, data ownership and protection, and privacy and integrity of self. This author proposes a new consideration should be "expanded to reflect a broader range of issues, and to indicate more clearly what needs to be done to address them" (28): 1) Ensure analytics accounts for all that is known about teaching and learning so data and analytics can contribute to learner success, 2) Improve data literacy skills so users can be sufficiently informed to give or withhold consent, 3) Identify potential risks in safeguarding data and taking action to limit them, 4) seek to understand ways analytics can increase rather than decrease the work of equity and justice, 5) increase understanding of the value, ownership, and control of data, increase the agency of learners and education in understanding and using educational data.

## Only As Good As How You Use it: Best Practices in Student Success to Inform Intervention

### Strategies for Learning: Metacognitive, Motivational, etc.

*McGuire, Saundra. "Close the Metacognitive Equity Gap: Teach All Students How to Learn." Journal of College Academic Support Programs, Spring/Summer 2021, Vol. 4, No. 1, Pp. 69-72., Aug. 2021, https://digital.library.txstate.edu/handle/10877/14189.*

McGuire suggests complicating our understanding of "educational equity" by considering a term she thinks of as "metacognitive equity." Metacognition requires an understanding of your own learning process far beyond memorization or other study skills: "planning, monitoring, controlling, and making adjustments" through strategies such as reflection and analysis of one's own learning strengths and weaknesses. She argues "that it is the gap in metacognitive strategies that contributes most to the persistent achievement gap and that all students must be taught how to learn." Students can be taught these strategies through campus learning centers, faculty-led sessions where students discuss learning strategies, or reading books about metacognition. The QEP working group has often discussed the need to design an early alert system that promotes student agency; drawing on this article suggests that student agency should be promoted not only in the context of an early-alert system, but also in the context of approaches to learning.

*Fong, Carlton J., et al. "LASSI's Great Adventure: A Meta-Analysis of the Learning and Study Strategies Inventory and Academic Outcomes." Educational Research Review, vol. 34, Nov. 2021, p. 100407, https://doi.org/10.1016/j.edurev.2021.100407.*

From the abstract: This 24-page paper is based on a meta-analysis of research about the relationships between learning and study strategies, specifically measured by the Learning and Study Strategies Inventory (LASSI). Their analysis showed that motivation strategies had the strongest correlations on GPA and persistence. Test taking strategies, addressing anxiety, and selecting main ideas had the strongest correlation with higher test scores. Again, this kind of article may have the biggest impact on the work of the QEP in the intervention phase and identifying what resources students may most benefit from being connected to.

*Lucas, Chris, et al. "Predicting and Supporting Student Performance in a High Fail and High Incompletion Course: An Exploratory Study of Introduction to General Chemistry." College Student Journal, vol. 55, no. 2, June 2021, pp. 135–44.*

A study that proposes modeling to predict which students are likely to DFW the introduction to chemistry course at an unidentified university. SAT/ACT/GPA were found to be predictors, Pell was not. Significant attention give to the importance of instructor in student success and by extension the importance of teaching methods based in learning research. Implications include the possible development of support programs/practices for students identified as likely to finish DFW.

### The Importance of Addressing Well-Being and Promoting Help-Seeking

*Brocato, Nicole, et al. Well-Being for Students with Minoritized Identities. American Council on Education, 2021, p. 33, https://www.acenet.edu/Documents/Well-Being-Minoritized-Identities.pdf.*

Even as JMU considers approaches to identify students in need of support and designs programs or communication to reach them, this article can serve as a reminder of the importance of addressing campus culture in addition to supporting individual students. The 26-page report from the Amercian Council on Education emphasizes that undergraduate students with minoritized racial and ethnic, gender, and sexual orientation identities have substantially lower subjective well-being levels than their peers with privileged identities (iv). It calls for a shift from accommodation and inclusion design to a fundamentally diverse design, and shares tools and frameworks to help institutional leaders enact change.

*Asher BlackDeer, Autumn, et al. "Depression and Anxiety among College Students: Understanding the Impact on Grade Average and Differences in Gender and Ethnicity." Journal of American College Health, vol. 0, no. 0, July 2021, pp. 1–12, https://doi.org/10.1080/07448481.2021.1920954.*

From the abstract: Some are beginning to call collegiate mental health a crisis. This student presents data about prevalence of anxiety and depression, and the significantly lower GPAs among students who were diagnosed but not treated as compared with those receiving treatment. Proposes further research into help-seeking behaviors and effect on GPA.

*Chen, Jason I., et al. "The Relationship of Perceived Campus Culture to Mental Health Help-Seeking Intentions." Journal of Counseling Psychology, vol. 63, no. 6, Nov. 2016, pp. 677–84, https://doi.org/10.1037/cou0000095.*

This article studies the impact of campus culture (attitude, barriers, stigma) on mental health help-seeking MHSS) behaviors in students. The research suggests that the campus culture matters and suggests programming and messaging to promote MHHS. How does this pertain to early alert at JMU? Mental health will likely be one component of early alert flags and an important aspect of the response--so thinking about how to promote a culture that supports MHHS could be an auxiliary or simultaneous consideration.

*Tichavakunda, Antar A. "Black Students and Positive Racialized Emotions: Feeling Black Joy at a Historically White Institution." Humanity & Society, July 2021, p. 01605976211032929, https://doi.org/10.1177/01605976211032929.*

From the abstract: Research of Black students' experiences at historically White institutions of higher education (HWIs) often focuses on Black students' negative emotions as a result of racist conditions. This paper examines their positive emotions and feelings and how they "experience 'Black joy' in an otherwise White space," in an effort to complicate the conversation about Black student experiences within HWIs. Participants identified being, achievement, and collectivity as sources of Black joy.

*Shyne, Cynthia. Perspectives of African American and Hispanic American Students on Academic Support Services. Walden University, 2021, https://scholarworks.waldenu.edu/dissertations/10683/.*

Shyne's dissertation identifies a need for culturally appropriate academic services for African American and Hispanic American students (AAHA) at the college being studied, which had recently received university status and was serving an increasingly diverse student body. Shyne investigated how AAHA student perceptions of academic support services influenced their use and asked students what suggestions they had that would increase their use of support services. Four themes emerged: lack of understanding of various academic supports; feelings of isolation, discomfort, or lack of belonging; and lack of consistency or accountability in accessing resources.

*Sarabia, Heidy, et al. "What Helps Students Get Help?: An Exploratory Analysis of Factors That Shape Undocumented College Students' Use of Academic Support Services." Journal of Latinos and Education, vol. 20, no. 3, July 2021, pp. 290–303, https://doi.org/10.1080/15348431.2021.1949994.*

From the abstract: This article uses regression analysis to identify factors contributing to engagement with academic support services among undocumented students. Findings include that campus integration is associated with increased odds of using academic support services.

*Campbell, Rosalyn, and Linda Long. "Culture as a Social Determinant of Mental and Behavioral Health: A Look at Culturally Shaped Beliefs and Their Impact on Help-Seeking Behaviors and Service Use Patterns of Black Americans with Depression." Best Practices in Mental Health, vol. 10, no. 2, Oct. 2014, pp. 48–62.*

From the abstract: This study looks at the impact of cultural beliefs—particularly that black people don't get depressed, don't trust doctors, or don't need a doctor for depression on help seeking and service use for depression among black Americans.

## Leveraging the Power of Networking: Professional Networks and Peer-to-Peer Networks

*Waite, Chelsea. Peer Connections Reimagined: Innovations Nurturing Student Networks to Unlock Opportunity. Paper, Christensen Institute (Clayton Christensen Institute for Disruptive Innovation), June 2021, p. 38, https://www.christenseninstitute.org/wp-content/uploads/2021/05/Peer-Connections.pdf.*

From emergency aid in a catastrophic weather event to career pipelines, peer networks and peer social capital can play a significant role in supporting learners as they advance toward a successful future based on their own goals. Peer networks can take the form of social support to foster belonging and identify formation, academic support to drive learning and keep each other on track, guidance support to explore options and ease transitions, and mental health support to promote wellbeing and reduce loneliness. A range of approaches are surfacing for ways to leverage social capital in peer networks. The report shares innovative tools and models, as well as identifying five important considerations for institutions interested in engaging in this work (3).

*Stwalley, Robert Merton, et al. Using Enhanced Professional Networks to Increase Overall Student Retention. 2021, https://peer.asee.org/using-enhanced-professional-networks-to-increase-overall-student-retention.*

From the abstract: Through an NSF-funded project modeled on a Web of Support characterization model based on work with Native American populations, promising STEM students with low socioeconomic status could apply for a $6,500 4-year scholarship in the Rising Scholars Program. Students attended a summer boot camp, assisted in a faculty members' lab, received mentoring, focused on communication skills and career selection, conducted a research project and an internship, and received support applying for an entry-level position after graduation. Data suggested first-generation students from low SES backgrounds were successful in STEM fields when provided structure and counseling. Scale-up was recommended.

## Designing and Refining Interventions Based on Predictive Models

*Milliron, Mark David, et al. "Insight and Action Analytics: Three Case Studies to Consider." Research & Practice in Assessment, vol. 9, 0 2014, pp. 70–89, https://eric.ed.gov/?id=EJ1062814.*

This article focuses on three case studies with Civitas partner institutions which bring together insight analytics with what Civitas calls action analytics, delivered through a suite of applications that leverage predictive models for intervention activities through strategically designed workflows and formats that help administrators, faculty, advisors, and students interact with data to understand risk, test interventions, and guide outreach (72). Interestingly, they point out that the action analytics in turn further inform and continuously improve the insight analytics.

The first case study, at an institution of >50,000 students, evaluated the effectiveness of intervention approaches in course success through an actions-analytics approaches delivered through an app and refined over the period of several pilot semesters using a control group. The interventions included emails, messaging, and calendar invites and responded to an institution-specific predictive model that Civitas developed (mostly based on SIS and LMS data). After several semesters of testing and refinement, students receiving the interventions outperformed the control group. The second case study, at an institution of >20,000, used predictive models to create daily engagement scores and focused on the potential of differentiated faculty outreach to improve student engagement and in turn, outcomes, in online courses. The third case study was conducted at a 4-year access institution with >40,000 undergraduate and graduate students to evaluate and refine scalable advisor/student success coach interventions not for course success, but for student persistence. The predictive model was continually updated through the course of a semester to incorporate new student behavior data. Among the lessons learned: that for students who were of greater concern for persistence, phone calls worked better than email; for students who were likely to persist, speaking with a student was only slightly more effective than email. In summary, as captured in a sidebar in the article, "We present three cases in an effort to show how this iterative work unfolds in diverse institutions, approaching diverse student success challenges, and to underscore a key finding: There is not a one–size– fits–all predictive model for higher education institutions. Each institution has its own predictive student flow and leaders, teachers, and advisors need to understand and engage their student success strategies in the context of their own students, policies and practices" (75).

## Other Resources

*Armatas, Christine, et al. "Learning Analytics for Programme Review: Evidence, Analysis, and Action to Improve Student Learning Outcomes." Technology, Knowledge and Learning, Aug. 2021, https://doi.org/10.1007/s10758-021-09559-6.*

From the abstract: A case study report of a project applying learning analytics to program curriculum review in a major cross-institutional project in Hong Kong, including description of project rationale, conceptual model, development of software tool, and challenges faced in data governance.

*Buyarski, Catherine, et al. "Learning Analytics Across a Statewide System." New Directions for Higher Education, vol. 2017, no. 179, 2017, pp. 33–42, https://doi.org/10.1002/he.20241.*

Abstract: "This chapter explores lessons learned from two different learning analytics efforts at a large, public, multicampus university—one internally developed and one vended platform. It raises questions about how to best use analytics to support students while keeping students responsible for their own learning and success."

*Smith, Dimitra J., et al. "Beyond Articulation Agreements: Fostering Success for Community College Transfer Students in STEM." Community College Journal of Research and Practice, vol. 0, no. 0, Aug. 2021, pp. 1–5, https://doi.org/10.1080/10668926.2021.1961923.*

From the abstract: Based on responses from more than 500 STEM students transferring between two-year and four-year colleges in a south-west alliance, transfer students indicate a need for support beyond articulation agreements, including knowledgeable advising and mentoring, lab equipment and study space, and opportunities to connect with professionals in industry and higher ed. Increasing faculty diversity, establishing a faculty diversity training and developing a writing center were other recommendations.

*Swanson, Elise, et al. "Examining the Relationship Between Psychosocial and Academic Outcomes in Higher Education: A Descriptive Analysis." AERA Open, vol. 7, Jan. 2021, p. 23328584211026970, https://doi.org/10.1177/23328584211026967.*

From the abstract: This study estimates the relationship between low-income background student psychosocial and academic outcomes during the first three years enrolled at public, 4-year institutions. Four psychosocial outcomes were measured across the three years: mattering to campus, sense of belonging, academic self-efficacy, and social self-efficacy. They were moderately predictive of academic outcomes, with sense of belonging and academic self-efficacy being the most predictive of both cumulative GPA and persistence.

# Appendix G: Literature Review Subgroup Values and Ethics Report

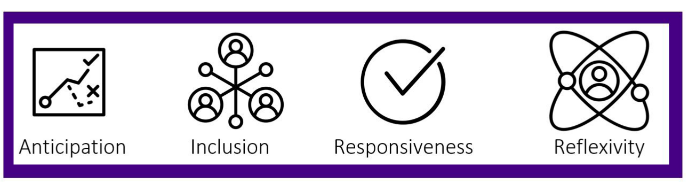
## Values and Ethics to Guide JMU's Early Alerts Development

The Early Alerts system is intended to identify students who may be at risk of withdrawing from the institution to support interventions that would increase retention rates and closing equity gaps. As such, it will integrate multiple forms of student-generated data, and this data will necessarily be identifiable. To design and implement such a system in ways that protect student privacy and well-being, and that promote JMU values, will require care and commitment throughout the design, implementation, and deployment phases.

The Early Alerts system can be understood as one form of learning analytics, which refers to "'the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing [sic] learning and the environments in which it occurs'" (Jones, 2019, 2, quoting Long & Siemens, 2011, 33). In the case of Early Alerts, the focus is not on classroom learning per se, but the entire learning environment—the campus—within which students' academic process is linked to a number of other factors in the context of retention. In this sense, it can also be understood as institutional analytics, or an institution-wide analytics system that enables administrators to access data and dashboards to track students across individual courses and to compare students (Jones, 2019, 4). Because systems geared toward retention may be designed to incorporate a wide variety of data, from classroom-based learning analytics to enrollment data to social media analytics, this section will use the umbrella term of 'data analytics', which should be understood in this context as data analytics implemented and used by the university.

## Process

Effectively implementing an ethical data analytics benefits from an ethical design process. This section recommends an evidence-based framework for responsible innovation that highlights four distinct categories of praxis: Anticipation, Inclusion, Responsiveness, and Reflexivity (AIRR) (Owen, et al., 2013). While the AIRR framework has been applied to many different areas related to innovation and technology, from genetically modified crops (MacNaghten, 2016) to STEM education (Tomblin and Mogul, 2020), to our knowledge it has not been applied to help universities navigate the complex challenges related to responsibly developing and implementing data analytics. One affordance of the AIRR framework is that it translates easily across the diverse group of actors and stakeholders that are involved in such projects, it is broad enough to be tailored to institutional needs, and it aligns with well-established practices for stakeholder-engaged development of projects and programs within a university setting.




Anticipation requires responsible innovators to assess multiple scenarios in relation to an innovation in order to proactively identify and analyze potential 'unintended consequences.' Anticipation recognizes that there is always the possibility of an unintended consequence. A robust anticipatory practice should make visible a variety of plausible use cases and analyze these in relation to different stakeholders, in order to determine whether design decisions in the innovation process can better maximize benefits and minimize harm. For anticipation, a guiding question is: What could go wrong with this implementation? This includes failure to achieve the goal, as well as the potential consequences of different assumptions and design decisions.

### What could go wrong with this implementation?

Inclusion refers to authentic engagement with all relevant stakeholders to guide decision-making with stakeholder input. Importantly, this should occur early in the process, when input still has the potential to shape outcomes. A guiding question here is: Who are the relevant stakeholders, and how can practices of inclusion attend particularly to those with the least power in the situation?

Who are the relevant stakeholders?

Responsiveness requires innovators to not only listen to stakeholders, but to genuinely work to integrate their insights and concerns. This does not necessitate acceding to every demand, but does imply addressing legitimate concerns in a robust way. Here, a key question is: How can design and implementation best incorporate input from relevant stakeholders, and insights gleaned by anticipating diverse scenarios?

### How can we best respond to stakeholder input?

Reflexivity signals the willingness of innovators to recognize the limits of their own perspectives, and to update their thinking in relation to the other three areas of praxis identified in AIRR. In other words, how can innovators make visible and transparent the assumptions and values that shape design and implementation? This also entails reflecting on decisions and documenting their rationales.

### How can we be transparent?

*Considerations*

While the university already gathers data about each student, there are several key aspects to a data-driven system that merit particular attention. First, consolidation of data into central and connected systems makes visible more aspects of a single student than when such data is collected and stored in a distributed and disconnected way. For example, the university as such may "know" when a single student misses multiple classes, when they use the university gym, when they go to the dining hall, and what they check out from the library. But when these data are disconnected, no meaning can be inferred about any relationship between these disparate facts. When this data is connected and analyzed, patterns might emerge: perhaps they checked out materials about depression, suddenly missed class and stopped going to the gym, and for the last two days has not been present in a dining hall. This might raise a flag of concern.

*Connecting data about a person creates significant, new privacy considerations as compared to the mere collection of data.*

However, this leads to a second consideration: while big data analytics can make visible patterns of correlation, this is a tool that does not provide the answer to the question of why. What a system user or analyst infers from a pattern may be incorrect. This student might have a paper due on mental health. Knowing that they could afford to miss a class or two, perhaps they went home to focus on writing this paper. Or, perhaps the student is concerned about a family member and has returned home, but is in no considerable danger themselves. Or, perhaps these events are entirely disconnected. They might have the flu, and friends are bringing them food. The difference between a correct and incorrect inference can result in harm when actions and interventions are taken based on a false narrative. Such harm can be individual, for example, decreasing a student's sense of belonging. It can also be aggregate, for example, if a disproportionate number of false narratives target a specific student demographic that results in a pattern of poor interventions. And, whether individual or aggregate, such harm can adversely affect the university – from negatively impacting stakeholder trust in the early alerts system itself to resulting in reputational harms or even legal liability for the university.

*Actions and interventions based on false inferences can result in harm*

Moreover, as previously indicated, a third consideration in the case of a system such as an early alerts system is that this data is not only connected in order to enable analytics, it is tied to the individual. In many learning analytics and data analytics projects, data might be de-identified. While there are increasingly tools to re-identify data, which is outside the scope of this report, in the case of a system designed to enable individual interventions the data is never de-identified to begin with. It can also be highly sensitive—this is a system that likely connects a student's personal information with physical and mental health data, educational data, social patterns, and more.

*Student data in the context of an Early Alerts system is, by design, identifiable*

This leads to a fourth consideration: Such data is consolidated and highly sensitive, which means that not only is there a potential of harm even when the system is being used correctly, the risk of a data breach is potentially considerably more damaging than in it might otherwise be. Whether in the case of normal use, i.e., the ways that the university might legitimately use the data as part of an early alerts system, or in the case of a breach, a student's privacy may be infringed upon. Privacy can be defined as: "…an individual's 'right to determine for themselves when, how, and to what extent information about them is communicated to others.' A control approach to privacy assumes not that information is absent in others' minds, but that we can determine who can access information about ourselves and limit to whom and under what conditions it is disclosed…. Privacy-as-control is biased toward individual choice and treats information as part of one's person." (Jones, 2019, 6). Student privacy should be addressed, therefore, both in relation to students' rights and in relation to outcomes that can always include data breaches.

*The sensitivity of such student data increases the potential harm of a security breach*

Even in the case of a secure system with multiple layers of protection to ensure a student's privacy and well-being, a data analytics system, as a technology designed and implemented by humans and deployed within an institution, reflects the assumptions, values, biases, and power relations within which it is designed, implemented, and deployed: "…We suggest that learning analytics be seen as 'a structuring device, [that is] not neutral, informed by current beliefs about what counts as knowledge and learning, coloured by assumptions about gender/race/class/capital/literacy and in service of and perpetuating existing or new power relations" (Prinsloo & Slade 2017d)" (Prinsloo and Slade, 2018). That is to say, while design, implementation, and evaluation, should strive to embody institutionally stated values, be transparent about assumptions, root out biases, and mitigate the harms of power dynamics, a human-designed system is necessarily a social product of its time and place, imbued with values and politics, that can have enormous governing power.

*Data analytics systems build in values and biases, even when this is unintentional*

These considerations raise legitimate questions about student agency. According to Reidenberg and Schaub, "For users to have control or agency, they must have awareness of the data practices and an ability to make decisions regarding participation" (Reidenberg & Schaub, 2018, 269). One way that many systems attempt to enable agency is through some form of informed consent. This refers to "…the process by which individuals are notified of how a secondary party, such as organizations (like a business) or institutions (like a university), will use information about them (Tene & Polonetsky, 2013, p. 260). It also informs them of their rights to privacy, as well as the express rights the second party retains regarding the information. After being informed of rights and information practices, individuals can then choose whether or not to agree—to consent—to the terms in front of them and enter into a relationship with the second party or not" (Jones, 2019, 7-8).

Yet, research on how informed consent might work in the context of data analytics in higher education suggests that there are unique challenges in this environment, and tradeoffs to be managed (Jones, 2019). For example, if students are allowed to opt in rather than to opt out—generally considered desirable from the perspective of privacy advocacy—this could result in lower levels of participation, which results in less data and a less robust data analytics system that does achieve the university's retention goals. Additionally, much of the data collected will be metadata. Metadata is the data about data. For example, in the case of a phone call, meta data refers to the times and phone numbers involved in an exchange but not the content of the call. In the case of a university, this complicates the question of how and when consent is pursued. Determining the appropriate level of granularity for requiring student consent entails questions of ethics that span concerns about university responsibility, student autonomy and rights, and the effectiveness (outcomes) of the entire system.

One question for this system, then, is how it can achieve its goals while supporting student agency and avoiding harm. According to Prinsloo and Slade, "…Student-centered learning analytics proceeds from the basis that students are not data-providers or data-points, but that they are and should be involved in determining what data would be valuable for them to make better informed decisions within their loci of control" (Prinsloo and Slade, 2018). Could an early alerts system be designed not just to enable appropriate interventions, but to support student learning and agency in relation to their own success at JMU?

Students are persons, not data objects

## Recommendations

1. Define an institution-wide set of principles and policies concerning learning analytics at James Madison University and make these publicly accessible.
2. Frame 'Early Alerts' as a student-centered success support system that foregrounds student agency and utility in supporting their own learning and success.
3. Proactively educate students on the benefits and risks of learning analytics, as well as their rights with respect to data usage at JMU.
4. Identify which data should be opt-in, which should be opt-out, and which should be neither. These decisions should be documented and should be aligned with the stated principles and policies.
5. Document all design decisions with rationales.
6. Implement a plan for evaluating and monitoring the system once it is live.

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# Appendix H: Literature Review Subgroup Learning Analytics and Big Data Report

## Introduction

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

## Influencers in Adoption of Predictive Models

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

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

## Data Sources

Developing algorithms for a predictive learning model is a complex endeavor and one that is unique to each university, so no two systems are the same. The complexity of code is dependent upon the objectives, available hardware and software and user experience. Research identifies three areas of data most used in predictive learning analysis including static, activity and achievement data (Alhadad et. al., 2015).

However, it is imperative that students are informed of what data is collected and how it is being used, as well as establishing data governance policies and processes for managing that data.

- Activity Data is considered the most significant predictor of student success.

  o Learning management system – LMS data examples include total login frequency, course absences, time spent in the system, number of downloads, interactions with peers, number of exercises performed, number of forum posts, duration of engagement with materials in the system, and assignment grades (Dietz-Uhler & Hurn, 2013, Mwalubwe & Mtebe, 2017).

  o Library systems and e-Textbooks – Newly identified contributors to learning analytics includes login frequencies, downloads, time spent within these systems, books checked out, and study rooms reserved (Oakleaf et. al., 2017).
- Achievement Data

  o Assignment/Mid-term grades – Student achievement data includes college level course completion rates, assignment grades and mid-term grades (Swaak, 2022).
- Static Data is beneficial but is considered the least effective predictor of student success (Sclater et. al., 2016).

  o Past academic performances – Past academic performances is a contributing factor when considering college level coursework.

  o Student survey data – Annual student survey data is included in many early-alert systems (Johnson et. al., 2012).

  o Student Information Systems – Data including courses undertaken, residency on-campus or off, and demographics with caution (Villano et. al., 2018).

## Dashboards

Institutions implementing a learning analytics initiative must consider the specific tools and accesses needed to collect, store, and analyze data as well as a dashboard to visualize the information in meaningful ways (Mah, 2015). Developing an effective dashboard design means considering factors beyond simple user and interface with the goal of providing cognitive and behavioral process-oriented feedback to learners and educators to initiate positive change (Sedrakyan et. al., 2018). Beyond technical capabilities, the designing team must understand the cognitive cues associated with data visualization, design best practices, as well as contain domain expertise in learning theories and paradigms (Susnjak et. al., 2022). The visualization technique needs to ensure the design is aesthetically pleasing, providing information in meaningful ways while not overwhelming the user (Susnjak et. al., 2022).

The platform must provide the learner with a clear understanding of the link between the data and the recommended intervention, and an opportunity to either opt-in or out of the systems empowering students with control over how their data is being used (Villano et. al., 2018). Users must accept and understand the information provided in order to take the appropriate action and ensure a successful outcome. The goal is to transform data into knowledge.

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