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A Proposed Framework for Referral, Early Identification, and Support of University Students with Potential Risks: A Case Study of a Historically Disadvantaged University in South Africa

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ABSTRACT

This paper presents a proposed framework for the early identification and support of students who may be at risk of not succeeding in their studies at a historically disadvantaged university in South Africa. The purpose is to address the critical need for a proactive, systematic approach to identifying students facing academic, social, or psychological challenges, thereby mitigating attrition and fostering student success. This research adopts a multi-faceted methodological approach, conducted at a single historically disadvantaged institution. Data was gathered through a series of engagement and focus group discussions with key university stakeholders, including academic advisors, counsellors, faculty members, and student academic support staff. The proposed design framework is built on the premise that data on student involvement, social well-being, and behavior patterns can be used to enhance student academic success.The paper proposes a multi-tiered referral framework that formalises collaboration between academic and support units. Key recommendations include the implementation of a centralised early-alert system, mandatory cross-departmental case meetings, and dedicated training for staff on identifying and referring at-risk students. This study contributes to the scholarship on student retention and support by presenting a context-specific framework tailored for the unique challenges of historically disadvantaged institutions. It moves beyond theoretical models of learning analytics by integrating them with a practical, stakeholder-driven referral mechanism. The research provides a replicable model for other similar institutions seeking to transition from reactive, crisis-management approaches to a proactive, holistic ecosystem that supports both student academic achievement and overall well-being.

Keywords: *Students at risk, data-driven, referral process, Student success, academic support, diagnosis*

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INTRODUCTION

In today's dynamic and complex higher education landscape, universities face the challenge of ensuring the well-being and success of their diverse student populations. A crucial aspect of this endeavor is the early identification and support of students who may be at risk of encountering academic, social, or psychological

difficulties.[1] Such challenges can hinder a student's academic progress and overall well-being, ultimately affecting their journey toward academic success and future success. Finding the circumstances in which school experiences can change students' social or academic development has significant ramifications for understanding the ways in which students can positively adapt at school.[2] To address this issue, there is a growing recognition of the need for efficient and effective referral systems that can identify students with potential risks and connect them with appropriate support mechanisms.[3] These systems leverage data-driven approaches to analyze a range of factors, including academic performance, engagement patterns, and behavioral indicators. According to the literature, retention in many schools and educational institutions nowadays is managed by responding to the behavior of the students.[4] However, it might be too late to keep that student in class by the time their challenge is identified.[5] Therefore, utilizing data-driven methods to examine a variety of aspects related to students' behavior is key. By systematically detecting early warning signs, universities can intervene proactively and provide timely assistance to students, thereby mitigating potential challenges before they escalate.[6]

The proposed system harnesses the power of technology, collaboration, and data analysis to create a structured framework for identifying and supporting students in need. It integrates insights from academic advisors, faculty members, student development and support services, and student counselors, to ensure a multidisciplinary approach that addresses the diverse range of challenges students may face.

In the subsequent sections, this paper shares insight from the existing work, delves into the conceptual underpinnings of the proposed referral system, and elaborates on its architecture, key components, and stages of operation. Additionally, the anticipated benefits of implementing such a system are explored, including improved student retention, enhanced overall well-being, and the cultivation of a responsive and supportive university community. By presenting this comprehensive framework for early detection and support, this paper contributes to the ongoing discourse on student success in higher education. It underscores the importance of a proactive and collaborative approach in creating an environment where every student can thrive and achieve their full potential.

LITERATURE REVIEW

This section reviews the existing literature to provide a comprehensive overview of relevant studies and best practices that contribute to the understanding and development of the referral system. Early warning systems have become well-known as useful resources for locating students who are at risk. Predictive analytics and data-driven models can help identify students who are showing early indicators of academic, social, or psychological difficulties.[7] These platforms give universities the ability to be proactive, which improves

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[1] N Phellecy Lavhelani, Clever Ndebele, and Fhatuwani Ravhuhali, "Examining the Efficacy of Student Academic Support Systems for 'at Risk'First Entering Students at a Historically Disadvantaged South African University," *Interchange* 51, no. 2 (2020): 137–56; Ricardo M. Meira Ferrão Luis, Martin Llamas-Nistal, and Manuel J. Fernández Iglesias, "On the Introduction of Intelligent Alerting Systems to Reduce E-Learning Dropout: A Case Study," *Smart Learning Environments* 9, no. 1 (October 22, 2022): 29, https://doi.org/10.1186/s40561-022-00210-0; Andile Mngqibisa, " Investigating Strategies for Assisting At-Risk School Learners in Historically Disadvantaged Backgrounds: A Case of Amathole Education District, Eastern Cape Province" (Walter Sisulu University, 2023).

[2] Bridget K Hamre and Robert C Pianta, "Can Instructional and Emotional Support in the First-Grade Classroom Make a Difference for Children at Risk of School Failure?," *Child Development* 76, no. 5 (September 1, 2005): 949–67, https://doi.org/10.1111/j.1467-8624.2005.00889.x.

[3] V. Balachandar and K. Venkatesh, "A Multi-Dimensional Student Performance Prediction Model (MSPP): An Advanced Framework for Accurate Academic Classification and Analysis," *MethodsX* 14 (June 2025): 103148, https://doi.org/10.1016/j.mex.2024.103148.

[4] Muhammad Adnan and Kainat Anwar, "Online Learning amid the COVID-19 Pandemic: Students' Perspectives.," *Journal of Pedagogical, Sociology and Psychology* 2, no. 1 (2020): 45–51; Marco Javier Suarez Baron, Juan Sebastian Gonzalez Sanabria, and Jorge Enrique Espindola Diaz, "Deep Neural Network (DNN) Applied to the Analysis of Student Dropout in a Higher Education Institution (HEI)," *Investigación e Innovación En Ingenierías* 10, no. 1 (2022): 202–14.

[5] Luis, Llamas-Nistal, and Iglesias, "On the Introduction of Intelligent Alerting Systems to Reduce E-Learning Dropout: A Case Study."

[6] J. Bryan Osborne and Andrew S.I.D. Lang, "Predictive Identification of At-Risk Students: Using Learning Management System Data," *Journal of Postsecondary Student Success* 2, no. 4 (July 10, 2023): 108–26, https://doi.org/10.33009/fsop_jpss132082.

[7] Ming Li et al., "Study-GNN: A Novel Pipeline for Student Performance Prediction Based on Multi-Topology Graph Neural Networks," *Sustainability* 14, no. 13 (2022): 7965; Nabila Sghir, Amina Adadi, and Mohammed Lahmer, "Recent Advances in Predictive Learning

student success and retention in higher education. According to the literature, accurate predictions of academic performance for individual students are essential to inform interventions. To achieve this goal, researchers have identified several important attributes for predicting student academic performance, such as aspects of a student's demographic and socioeconomic background (e.g., place of birth, disability, parents academic and job background, residing region, gender, socioeconomic index, health insurance, frequency of going out with friends, financial status.[8] The idea of multi-tiered support models emphasizes the necessity of teamwork between academic advisers, teachers, counselors, and specialized support services.[9] Recent research in the United States has demonstrated the value of comprehensive and integrated programs that combine several interventions to create a seamless learning environment for supporting students academically, socially, and personally.[10] Such comprehensive approaches recognize that possible dangers might appear in many different areas of a student's life and that responses should be individualized.

According to research, there is a link between student engagement and academic achievement.[11] Students who are actively engaged have higher chances of thriving. To identify disengaged students who may be at risk, an efficient referral system should include engagement measures, as predictive models now utilize student behavior in learning management systems, including interactions with videos, assignment submissions, and participation in forums, to assess engagement and its impact on academic success**.** In the literature, significant attention has been paid to university students' academic performance, mental health, and well-being.[12] It is critical to recognize and assist students who are struggling with their mental health, as this may affect their academic performance.[13] Mechanisms for spotting indicators of mental distress and connecting students to counseling services should therefore be included in a referral system. On the other hand, research focuses on identifying students who are at risk of struggling academically and potentially dropping out of college by presenting models that can identify the risk of failing specific courses and those who stop academically.[14] By including data specific to these groups of students, educators, and educational institutions can better understand the unique challenges and opportunities that these students face and provide

Analytics: A Decade Systematic Review (2012–2022)," *Education and Information Technologies* 28, no. 7 (2023): 8299–8333; Priya Darshini, "Data Analysis and Prediction of Student Academic Performance," *Health Leadership and Quality of Life* 3, no. 424 (2024): 1.

[8] Osborne and Lang, "Predictive Identification of At-Risk Students: Using Learning Management System Data"; Abhinav Jain and Shano Solanki, "An Efficient Approach for Multiclass Student Performance Prediction Based upon Machine Learning," in *2019 International Conference on Communication and Electronics Systems (ICCES)* (IEEE, 2019), 1457–62, https://doi.org/10.1109/ICCES45898.2019.9002038; Tuti Purwoningsih, Harry B Santoso, and Zainal A Hasibuan, "Online Learners' Behaviors Detection Using Exploratory Data Analysis and Machine Learning Approach," in *2019 Fourth International Conference on Informatics and Computing (ICIC)* (IEEE, 2019), 1–8; Sandra Milena Merchan Rubiano and Jorge Alberto Duarte Garcia, "Analysis of Data Mining Techniques for Constructing a Predictive Model for Academic Performance," *IEEE Latin America Transactions* 14, no. 6 (June 2016): 2783–88, https://doi.org/10.1109/TLA.2016.7555255; V Shanmugarajeshwari and R Lawrance, "Analysis of Students' Performance Evaluation Using Classification Techniques," in *2016 International Conference on Computing Technologies and Intelligent Data Engineering (ICCTIDE'16)* (IEEE, 2016), 1–7; Warit Tenpipat and Khajonpong Akkarajitsakul, "Student Dropout Prediction: A KMUTT Case Study," in *2020 1st International Conference on Big Data Analytics and Practices (IBDAP)* (IEEE, 2020), 1–5, https://doi.org/10.1109/IBDAP50342.2020.9245457; Hassan Zeineddine, Udo Braendle, and Assaad Farah, "Enhancing Prediction of Student Success: Automated Machine Learning Approach," *Computers & Electrical Engineering* 89 (January 2021): 106903, https://doi.org/10.1016/j.compeleceng.2020.106903.

[9] Vincent Tinto, "Enhancing Student Success: Taking the Classroom Success Seriously," *Student Success* 3, no. 1 (2012): 1.

[10] Adrianna Kezar and Elizabeth Holcombe, "Integrated and Comprehensive Student Support Programs Aimed at Historically Underserved Students: Creating a Unified Community of Support," *International Journal of Chinese Education* 7, no. 1 (2018): 65–84.

[11] George D Kuh et al., "Unmasking the Effects of Student Engagement on First-Year College Grades and Persistence," *The Journal of Higher Education* 79, no. 5 (2008): 540–63.

[12] Kuh et al., "Unmasking the Effects of Student Engagement on First-Year College Grades and Persistence"; Tinto, "Enhancing Student Success: Taking the Classroom Success Seriously"; Camelia Stăiculescu and Richiteanu Nastase Elena Ramona, "University Dropout. Causes and Solution," *Mental Health: Global Challenges Journal* 1, no. 1 (March 3, 2019): 71–75, https://doi.org/10.32437/mhgcj.v1i1.29; Catherine Picton et al., "A Third Space Approach to Integrated Academic Student Success Advising (ASSA)," *Student Success*, September 18, 2023, https://doi.org/10.5204/ssj.2855.

[13] Daniel Eisenberg, Justin Hunt, and Nicole Speer, "Mental Health in American Colleges and Universities," *Journal of Nervous & Mental Disease* 201, no. 1 (January 2013): 60–67, https://doi.org/10.1097/NMD.0b013e31827ab077; Aimé Anita Jacqueline, "Mental Health Support in Schools: Addressing the Growing Needs of Students," *Research Output Journal of Education* 3, no. 3 (n.d.): 29–33.

[14] Osborne and Lang, "Predictive Identification of At-Risk Students: Using Learning Management System Data."

targeted interventions to support them.[15] Hence, universities may now use massive datasets to identify potential dangers because of developments in learning analytics and technology. The importance of learning analytics in comprehending patterns of student involvement and behavior is highlighted in the literature.[16] Learning analytics is student-centered and gathers information from student information systems and course management systems to monitor student success, including early warning systems where the need for interventions may be necessary.[17] The most popular learning analytics approaches, concentrate on the investigation of the underlying relationships between interactions and students' academic performance.[18]

Over the past few years, the creation of correlation and prediction analytics algorithms that use student data mining to find at-risk students has grown significantly. Researchers in a variety of fields, including education, computer science, and data analytics, have created these models, and they have shown encouraging results in identifying students who may be experiencing academic difficulties.[19] Some of the most recent notable studies in this area have demonstrated that by analyzing various student data points, such as grades, attendance records, and participation in extracurricular activities, it is possible to identify students who may be at risk of academic failure.[20] For implementation and efficiency, these resources should be utilised via a well-thought-out referral mechanism to improve precision, monitoring, and effective support for students in institutions of higher education.

Ethical issues in the use of learning analytics

The use of learning analytics presents various ethical issues that need to be considered, especially when dealing with students' data. These include issues such as privacy, confidentiality of individual data, as well as ethical considerations in the use of data. To protect personal data, organizations must comply with the condition of protecting individuals' personal information accordingly.[21] Addressing ethical issues with data privacy, consent, and equity is necessary before implementing a referral system. In the context of the South African higher education system, historically disadvantaged universities (HDUs) draw most students from traditionally disadvantaged backgrounds with various socio-economic challenges.[22] To avoid unfairly

[15] Fadhilah Ahmad, Nur Hafieza Ismail, and Azwa Abdul Aziz, "The Prediction of Students' Academic Performance Using Classification Data Mining Techniques," *Applied Mathematical Sciences* 9, no. 129 (2015): 6415–26; Osborne and Lang, "Predictive Identification of At-Risk Students: Using Learning Management System Data"; Darshini, "Data Analysis and Prediction of Student Academic Performance."

[16] Wolfgang Gaebel and Mathias Riesbeck, "Are There Clinically Useful Predictors and Early Warning Signs for Pending Relapse?," *Schizophrenia Research* 152, no. 2–3 (February 2014): 469–77, https://doi.org/10.1016/j.schres.2013.08.003; Farheen Islam et al., "Factors Influencing Academic Performance: An Empirical Study Using Predictive Analytics," *Multidisciplinar (Montevideo)* 3 (January 1, 2025): 51, https://doi.org/10.62486/agmu202551.

[17] Angela Van Barneveld, Kimberly E Arnold, and John P Campbell, "Analytics in Higher Education: Establishing a Common Language," *EDUCAUSE Learning Initiative* 1, no. 1 (2012): l–ll.

[18] Cheryl Ramos and Errol Yudko, "'Hits'(Not 'Discussion Posts') Predict Student Success in Online Courses: A Double Cross-Validation Study," *Computers & Education* 50, no. 4 (2008): 1174–82; Colin Beer, David Jones, and Ken Clark, "The Indicators Project Identifying Effective Learning: Adoption, Activity, Grades and External Factors," in *Ascilite*, 2009, 60–70; Félix Pascual-Miguel et al., "A Characterisation of Passive and Active Interactions and Their Influence on Students' Achievement Using Moodle LMS Logs," *International Journal of Technology Enhanced Learning* 3, no. 4 (2011): 403–14; Mihaela Cocea and Stephan Weibelzahl, "Cross-System Validation of Engagement Prediction from Log Files," in *European Conference on Technology Enhanced Learning* (Springer, 2007), 14–25; Leah P Macfadyen and Shane Dawson, "Mining LMS Data to Develop an 'Early Warning System' for Educators: A Proof of Concept," *Computers & Education* 54, no. 2 (2010): 588–99.

[19] Osborne and Lang, "Predictive Identification of At-Risk Students: Using Learning Management System Data."

[20] Gökhan Akçapınar et al., "Developing an Early-Warning System for Spotting at-Risk Students by Using EBook Interaction Logs," *Smart Learning Environments* 6, no. 1 (2019): 4; Tatiana Cardona et al., "Data Mining and Machine Learning Retention Models in Higher Education," *Journal of College Student Retention: Research, Theory & Practice* 25, no. 1 (2023): 51–75; Baron, Sanabria, and Diaz, "Deep Neural Network (DNN) Applied to the Analysis of Student Dropout in a Higher Education Institution (HEI)"; Sandeep Trivedi, "Improving Students' Retention Using Machine Learning: Impacts and Implications," *ScienceOpen Preprints*, 2022.

[21] Republic of South Africa, *Protection of Personal Information Act No. 4 of 2013* (Pretoria: The Presidency., 2013).

[22] Clever Ndebele, Munienge Mbodila, and Muhandji Mbodila, "Assessing Options for ICTs Integration in the Classroom at a Rural Based South African University," *Journal of Gender, Information and Development in Africa* 8, no. 2 (August 15, 2019): 37–58, https://doi.org/10.31920/2050-4284/2019/8n2a3; Rushiella N Songca, Clever Ndebele, and Munienge Mbodila, "Mitigating the Implications of Covid-19 on the Academic Project at Walter Sisulu University in South Africa: A Proposed Framework for Emergency Remote Teaching and Learning," *Journal of Student Affairs in Africa* 9, no. 1 (2021): 41–60.

targeting vulnerable students, the importance of transparency and appropriate data usage in student support efforts can not be overemphasised.[23]

The effectiveness of referral mechanisms is greatly influenced by campus culture.[24] Just because programs and practices are available does not ensure that they will have the desired effects on student progress; hence, institutional policies and procedures must be tailored to the requirements of the students they are designed to serve, and deeply ingrained in a campus culture that prioritizes student success.[25] A culture that promotes ethical behavior, diversity, and well-being should be part of a referral system. The core business of the university is to respond to student needs ethically; values such as honesty, integrity, respect, and ubuntu were considered in the development of the proposed referral framework to ensure ethical practices as well as to develop campus culture in pursuit of excellence.[26]

Challenges to consider in supporting potential risks

Supporting early possible risks among university students is a difficult task that requires dealing with several factors. The literature covers these issues in detail, illuminating the complex nature of student performance and well-being.[27] Not all students who display specific behaviors or academic patterns are in danger.[28] False positives may result in stigmatization or pointless interventions. This problem is highlighted in previous studies, and highlights the significance of improving algorithms to guarantee precise risk identification.[29] A caution to be emphasised, however, is that the same algorithms may show different performances for different data sets.[30] Universities cater for various student populations with a range of requirements, challenges, and origins. A one-size-fits-all strategy may neglect the requirements of some groups, highlighting the value of customized approaches as emphasized by Harper and Quaye.[31] Therefore, it is recommended to use ensemble learning models that combine the predictions of different algorithms to exceed the generalization capability and the robustness of a single learning algorithm and to make more accurate predictions.[32]

Another challenge is the stigma attached to getting support, students could be reluctant to ask for assistance. Studies show how stigma affects students' decisions to seek either academic support or mental health treatment.[33] Most students find it difficult to seek help and adapt at the university, especially those in

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[23] Ann Jones, Rebecca Aylward, and Aled Jones, "Enhanced Supervision: New Ways to Promote Safety and Well-Being in Patients Requiring One-to-One or Cohort Nursing," *Nursing Management* 32, no. 5 (2025).

[24] Mhlonishwa Khumalo and Reward Utete, "Factors That Influence Academic Performance of Students: An Empirical Study," *The Seybold Report* 18, no. 106 (2023): 1710–22.

[25] Vicki Trowler, "Student Engagement Literature Review," *The Higher Education Academy* 11, no. 1 (2010): 1–15; J Deysolong, "Assessing the Effectiveness of Interventions for Students with Learning Difficulties or Special Needs," *Australian Journal of Learning Difficulties*, 2023; Chima Abimbola Eden, Onyebuchi Nneamaka Chisom, and Idowu Sulaimon Adeniyi, "Cultural Competence in Education Strategies for Fostering Inclusivity and Diversity Awareness.," *International Journal of Applied Research in Social Sciences* 6, no. 3 (March 17, 2024): 383–92, https://doi.org/10.51594/ijarss.v6i3.895.

[26] Walter Sisulu University, *WSU Draft 2020-30 Strategic Plan* (Umtata: WSU, 2020).

[27] Kuh et al., "Unmasking the Effects of Student Engagement on First-Year College Grades and Persistence"; Tinto, "Enhancing Student Success: Taking the Classroom Success Seriously"; Eisenberg, Hunt, and Speer, "Mental Health in American Colleges and Universities"; Israel Creleanor Mulaudzi, "Factors Affecting Students' Academic Performance: A Case Study of the University Context," *Journal of Social Science for Policy Implications* 11, no. 1 (2023): 18–26.

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[29] Michael Waring and Carol Evans, *Understanding Pedagogy* (Routledge, 2014), https://doi.org/10.4324/9781315746159.

[30] Mohammad Noor Injadat et al., "Systematic Ensemble Model Selection Approach for Educational Data Mining," *Knowledge-Based Systems* 200 (July 2020): 105992, https://doi.org/10.1016/j.knosys.2020.105992.

[31] Shaun R Harper and Stephen John Quaye, "Beyond Sameness, with Engagement and Outcomes for All," *Student Engagement in Higher Education* 1 (2009).

[32] Halit Karalar, Ceyhun Kapucu, and Hüseyin Gürüler, "Predicting Students at Risk of Academic Failure Using Ensemble Model during Pandemic in a Distance Learning System," *International Journal of Educational Technology in Higher Education* 18, no. 1 (2021): 63.

[33] Patrick Corrigan, "How Stigma Interferes with Mental Health Care.," *American Psychologist* 59, no. 7 (2004): 614; T. Mthengi, " The Impact of the Extended Curriculum Programme on Learning by Students in the Extended Curriculum Programme in the Eastern Cape Province of South Africa : A Case Study" (Walter Sisulu University, 2025).

their first year.[34] Higher education institutions must foster a culture in which asking for assistance is accepted as normal. To implement and nurture such initiatives, there is a need for collaboration across multiple university departments, including academic advisors, faculty, counsellors, and administrators, for effective monitoring and support systems. Often, specialised units in universities tend to 'own' specific data which are analysed in separation from other possible data and information sources found in other parts of the organization.[35] Such silo mentalities among student support units can make attaining seamless interdisciplinary teamwork difficult. In addition to the above, the implementation of efficient early detection and assistance systems can be hampered by resource constraints.

Among other challenges, universities may find it difficult to train, employ additional support services, and fund modern technology systems and tools, which could affect how scalable and long-lasting these programs are. It takes computer skills in data interpretation and contextual knowledge in various areas to analyze student data to find potential dangers. The necessity of digital and data literacy, as well as experienced analytics personnel, highlights the fact that improper data interpretation can result in inaccurate conclusions and unsuccessful intervention. Often, the limited impact seen of learning analytics and other similar approaches is related to the limitations of data put into the analysis, and a lack of incorporating data and information which is also relevant to understand student performance is due to poor digital and data literacy[36].

As indicated in the literature, some of the challenges that impact student performance can be internal, for example, student competencies and attitudes and some can be external, for example, extracurricular academic factors, socio-economic, psychological and environmental.[37] Some of the challenges and factors may be of a social nature, such as student background and income levels; psycho-pedagogical, incorporating aspects such as inadequate academic training, underpreparedness for university studies, lack of counseling services, and personal, for example, poor adaptability to the university due to poor transition support.[38] Figure 1 displays a summary of categories of challenges that give a holistic overview of the areas that need to be looked at when dealing with students considered to be potentially at risk of failure in their studies.

[34] Munienge Mbodila, "On Overcoming Transitional Challenges of First Year Students in Technology-Based Educational Settings," *International Journal of Modern Education and Computer Science* 8, no. 11 (November 8, 2016): 28–35, https://doi.org/10.5815/ijmecs.2016.11.04.

[35] Bjørn Stensaker, "Building Institutional Capacity for Student Competencies: An Organizational Perspective," *International Journal of Chinese Education* 10, no. 1 (January 1, 2021), https://doi.org/10.1177/22125868211006200.

[36] Stensaker, B. (2021). Building institutional capacity for student competencies: An organizational perspective. *International Journal of Chinese Education, 10*(1), 1-10. https://doi.org/10.1177/22125868211006200

[37] Kuh et al., "Unmasking the Effects of Student Engagement on First-Year College Grades and Persistence"; Tinto, "Enhancing Student Success: Taking the Classroom Success Seriously"; Ihssan Abdulkadhum Jabor AL-Muslimawi and Azhar Adhiem Hamid, "External and Internal Factors Affecting Student's Academic Performance," *The Social Sciences* 14, no. 4 (October 31, 2019): 155–68, https://doi.org/10.36478/sscience.2019.155.168; Stăiculescu and Elena Ramona, "University Dropout. Causes and Solution."

[38] Stăiculescu and Elena Ramona, "University Dropout. Causes and Solution."

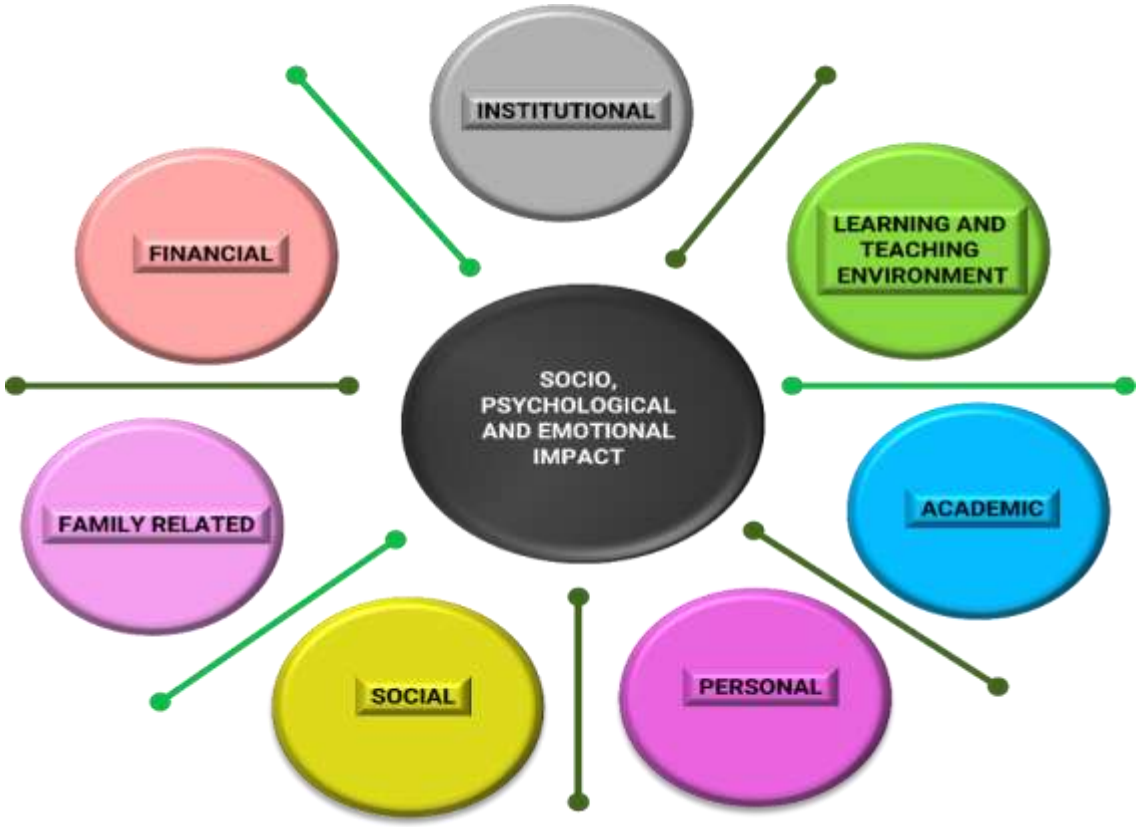

Figure 1: Challenges to Consider in Supporting Students with Potential Risks

Identification and intervention process for students with potential risks

The process of identifying and helping students who may be at risk includes a methodical strategy that incorporates data analysis, stakeholder cooperation, and specialized support systems.[39] When using learning analytics, there is a need to obtain pertinent information about students from registration to their graduation day. In the context of an institution, students' data must be collected from a variety of sources in the institution's system. Students' data related to test results, attendance records, participation in extracurricular activities, online activity, and other relevant interventions need to be collected to find patterns, trends, and anomalies that could point to dangers, using data analytics approaches.

To monitor the progress of students who need interventions, there is a need to put in place a continuous monitoring system to determine regularly if the interventions are successful in reducing the indicated risks.[40] In addition, it is essential to provide continual assistance and adjust methods as necessary, as well as create a feedback loop so that interested parties may weigh in on the success of the identification and intervention process. To support students with potential risks, the following flow process was developed by the university under study to identify and provide timely intervention guidelines for students.

[39] Kuh et al., "Unmasking the Effects of Student Engagement on First-Year College Grades and Persistence"; Tinto, "Enhancing Student Success: Taking the Classroom Success Seriously"; Islam et al., "Factors Influencing Academic Performance: An Empirical Study Using Predictive Analytics."

[40] Islam et al., "Factors Influencing Academic Performance: An Empirical Study Using Predictive Analytics."

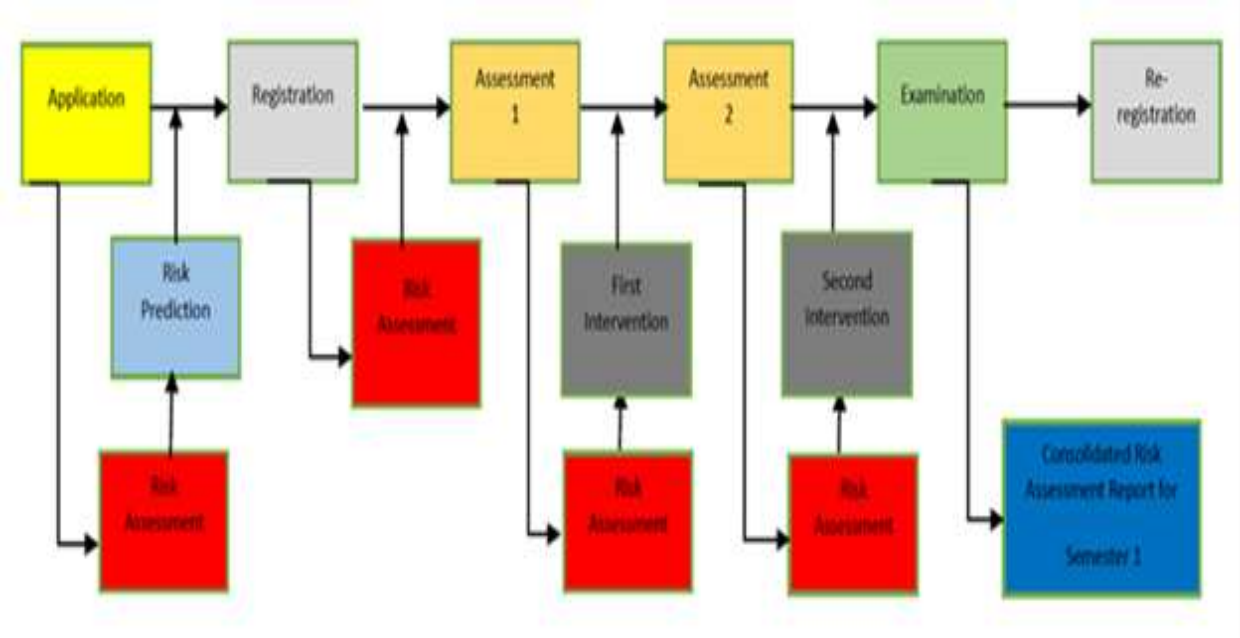

Figure 2: Identification and Intervention Process Flow of Students at Risk [41]

From the above flowchart, assessing the effectiveness of the identification and intervention procedure regularly is one of the key strategies in the identification and intervention process presented in this study. Based on the severity of the identified risks, well-developed tailored interventions are provided. These interventions could include academic support workshops, counseling sessions, time management workshops, mentorship programs, or referrals to external resources such as mental health professionals. In the context of the institution under the current case study, the Directorate of Learning and Teaching (DLT) and Student Development and Support Services (SDSS) have specific resources targeted at supporting students academically, psychologically/emotionally, and ensuring that their well-being is fit. These referral sources are displayed in Figure 3.

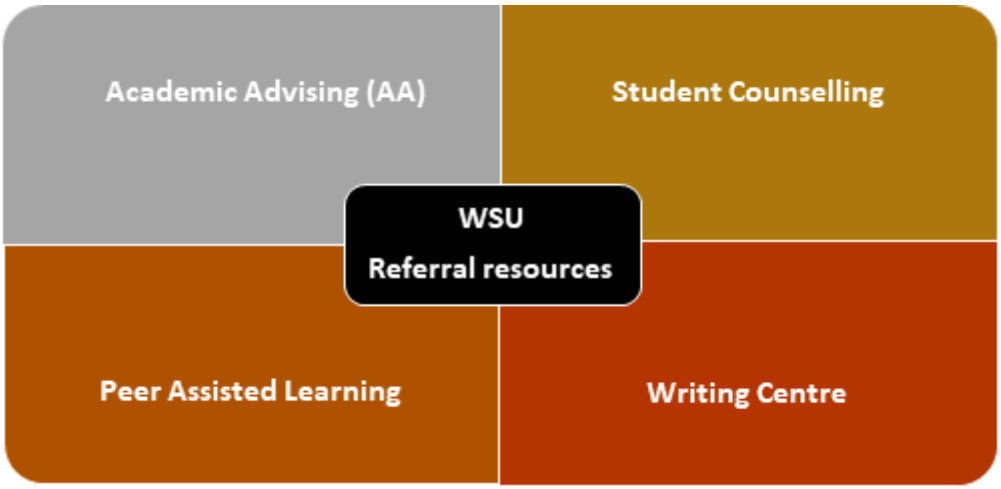

Figure 3: Referral Resources (Source: The Authors)

[41] Walter Sisulu University, *WSU Draft 2020-30 Strategic Plan*.

The Directorate of Learning and Teaching (DLT) and Student Development and Support Services (SDSS work closely with faculties and academics when it comes to students-at-risk referrals to ensure that proper and timely interventions are put in place. This ensures that all data collection and intervention processes in the various referral resources adhere to data privacy regulations and ethical considerations.

METHODOLOGY

The proposed framework was conceptualised through a multi-faceted methodological approach, which included a comprehensive review of institutional policies and existing support protocols and benchmarking against local and international institutions. A series of engagement and focus group discussions with key university stakeholders, including academic advisors, student counsellors, faculty members, and student support. In addition, the framework was presented at the university's student success committee meeting where further input helped to refine it.

Proposed framework for a referral system for early identification of at-risk students

A referral is a sequential process or procedure that must be followed to ensure that students with potential risk receive the necessary support that is needed.[42] The support can be in different forms depending on the identified gaps. In the context of education systems, it's important to note that the specifics of a referral system can vary widely depending on the educational institution and its goals. The effectiveness of such systems also depends on their implementation and the availability of resources to support referred students.[43] In the context of the institution under study, the support for referred students can be from an academic advisor, student counselling officer, peer-assisted learning coordinator, writing center coordinator or faculty in line with the referral resources provided by the institution. The university has various systems that gather a range of pertinent student data from many sources. For analysis, this data is included in a centralized platform or database managed by the student tracking unit, which oversees identifying students and modules with potential risks. This data is used for multi-tiered referral procedures after a referral is triggered.

The design of the proposed framework ensures that several university stakeholders are involved, including academic advisers, faculty members, counselors, and support services. The prescribed actions and interventions at each stage of the process are in line with how serious the danger is. As such, for an effective referral system, all stockholders responsible for students' support are encouraged to develop an integrated approach to ensure befitting interventions are devised and put in place. Below is the flowchart of the proposed referral framework system at the institution under this case study:

[42] Bernice Ofosu et al., "Assessing the Functionality of an Emergency Obstetric Referral System and Continuum of Care among Public Healthcare Facilities in a Low Resource Setting: An Application of Process Mapping Approach," *BMC Health Services Research* 21, no. 1 (2021): 402.

[43] Shailini Dixit, Md. Alimul Haque, and Priya Darshini, "Predictive Analytics in Education: Modeling the Complex Relationship Between Learning Modalities and Student Well-Being," *EthAIca* 4 (July 27, 2025): 203, https://doi.org/10.56294/ai2025203.

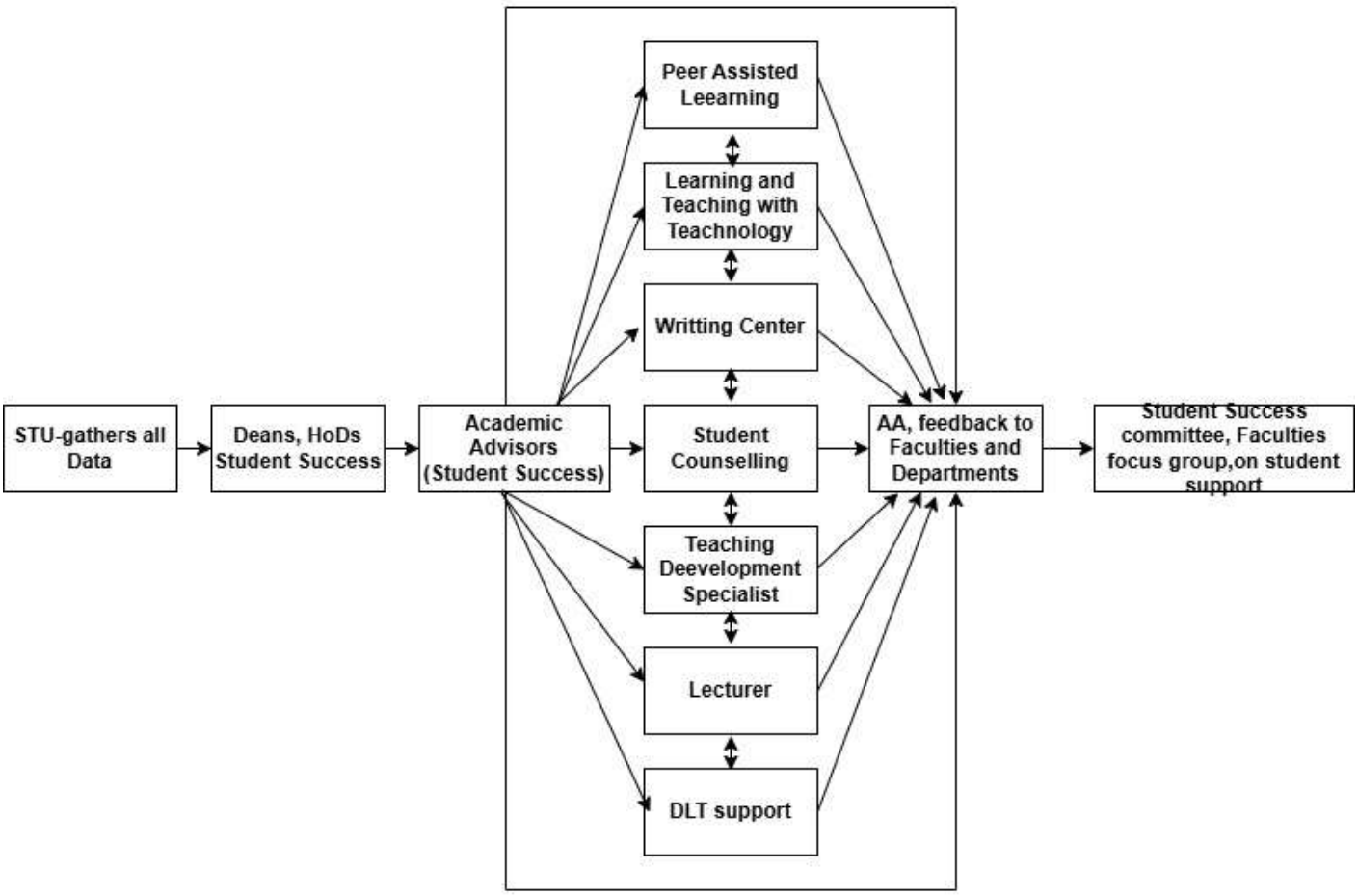

Figure 4: Proposed framework for a referral system for early identification of at-risk students

From the above components of the proposed framework for the referral system, during each tier of the referral process, stakeholders collaborate to make informed decisions. They discuss the student's situation, review available data from the student tracking unit, and determine the most appropriate course of action. This collaborative approach ensures that interventions are well-informed and holistic. Students who receive interventions are monitored closely. Their progress is tracked over time to assess the effectiveness of the interventions. Regular follow-up meetings or check-ins ensure that students are making positive strides toward addressing their challenges. By incorporating these components in the proposed framework for the referral system, the aim is to proactively identify and support university students with potential risks, ensuring their well-being and academic success. In this process, we provide an explication of the roles of the various stakeholders in Figure 4 and Table 1.

Table 1: Stakeholders and Roles as depicted in Figure 4

Stakeholders	Roles
Student Tracking Unit (STU)	Collects and tracks student data; Provides feedback to faculties and related support services portfolios, facilitates the development of interventions.
Faculty Dean	Follows up on submission/Capturing dates for test marks timeously by lecturers. Assists departments in designing intervention strategies for identified risks.

Head of Department (HOD)	Monitors reports of student tracking and modules at risk. Monitors the implementation of interventions for students and modules at risk. Sets up interventions meetings with students and lecturers.
Student Success Manager	Provides capacity building for students appointed as mentors and tutors of students at risk. Coordinates the implementation and monitoring of interventions for students at risk.
Lecturer	Works with student mentors to implement intervention strategies for students identified as at risk. Submits/captures test marks immediately after the test to allow a smooth process of data collection by STU.
Academic Advisor (AA)	Contacts "At-risk" students based on data received from STU. Keeps accurate records of calls and any attempts at communication by at-risk students. Sets up academic advising sessions with students, keeps records of meeting procedures and advice/referrals given to individual students, and conducts follow-up sessions with stakeholders where students have been sent for referral. Submits reports of intervention measures to relevant stakeholders, for example, the HOD or the lecturer.
Teaching Development Specialist (TDS)	Contacts lecturers of "At-risk" students and discuss possible intervention measures. Condcuts capacity development sessions with lecturers on assisting 'at risk' students. Conducts evaluation of teaching and courses by students. Provides curriculum support to lecturers where students, for example, indicate during evaluation of teaching that the curriculum content is way above their levels of cognition, as this could be a cause of poor student success performance. Sets up academic development sessions with lecturers on learning pedagogies that promote student learning.
Student Counselling	Provide student health and well-being services, Student counselling, psychological help, and student mentorship.
Writing Centre Coordinator	Analyses data on student performance in university and from national access tests and shares the data with lecturers. Provides writing support to students who may be failing in their studies due to language issues.
Learning & Teaching with Technology Unit	Supplies data from the Learning Management System (LMS) to the Student Tracking Unit on student assessments. Monitors student participation in actual classes/live sessions through the LMS and shares this data with STU and lecturers.
Peer-Assisted Learning Coordinator	Analyses data from the student tracking unit on student academic challenges. Puts in place an institution-wide peer-assisted learning program where senior students who have done well in particular modules assist students who are struggling in those modules. Incentivises peer-assisted learning by student assistants through a stipend.

CONCLUSION

The Referral System for Early Detection and Support of University Students with Potential Risks that has been presented is an essential step in creating a supportive and flexible learning environment. This proposed framework has the potential to revolutionize how universities approach the success and well-being of their students by using the power of data-driven analysis, interdisciplinary cooperation, and personalized interventions. The core of the proposed framework consists of its capacity to foresee potential risks at an early stage, enabling prompt and specialized actions. It enables the university to proactively address academic, social, and psychological issues that students may encounter challenges with by utilizing cutting-edge technology and a wide range of data sources. This proactive approach fosters a culture of caring,

empathy, and support within the institution while simultaneously reducing the negative effects of potential dangers. Furthermore, the proposed system goes beyond identification alone. Its multi-tiered referral process ensures that each student's situation is thoroughly evaluated and responded to by the appropriate stakeholders. The collaborative decision-making approach guarantees that interventions are well-informed, effective, and aligned with each student's unique needs. As universities strive to enhance student retention and success, as well as overall well-being, the benefits of the proposed referral framework system for early detection and support become evident. By promoting a positive campus culture, improving academic support and social well-being support, as well as fostering equity and inclusion, the proposed referral system aligns with the evolving needs of diverse student populations.

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