Advising at Scale: Automated Guidance of the Role Players Influencing Student Success

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About the Authors

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Abstract

Although student advising is known to improve student success, its application is often inadequate in institutions that are resource constrained. Given recent advances in large language models (LLMs) such as Chat Generative Pre-trained Transformer (ChatGPT), automated approaches such as the AutoScholar Advisor system affords viable alternatives to conventional modes of advising at scale. This article focuses on the AutoScholar Advisor system, a system that continuously analyzes data using modern methods from the fields of artificial intelligence (AI), data science, and statistics. The system connects to institutional records, evaluates a student's progression, and generates advice accordingly. In addition to serving large numbers of students, the term "advising at scale" refers to the various role players: the executives (whole-institution level), academic program managers (faculty and discipline levels), student advisors (faculty level), lecturers (class level), and, of course, the students (student level). The form of advising may also evolve to include gamification elements such as points, badges, and leaderboards to promote student activity levels. Case studies for the integration with academic study content in the form of learning pathways are presented. We therefore conclude with the proposition that the optimal approach to advising is a hybrid between human intervention and automation, where the automation augments human judgment.

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INTRODUCTION

Traditional academic advising in a one-advisor-to-one student approach is resource intensive and difficult to sustain, prompting institution officials to develop alternative student advising models (Thiry & Laursen, 2011). This approach uses analytics to sort students by their likelihood to drop out or stop out, which allows advisors to prioritize their time in favor of students that face rising risk. Networks of advisors, faculty, and other student support leaders form teams that can effectively address the complex needs of students. This approach allows for efficient use of resources and a focus on individualized academic advising (EAB, 2023).

Although institution officials continue to offer ongoing support programs such as orientations, tutoring, and learning centers (Bornschlegl et al., 2020), such resources typically require students to actively seek out those programs (Fong, 2021). Many universities struggle to develop and maintain effective advising services that promote student satisfaction and increase student retention (Anderson et al., 2014). In response, there has been an ascendancy of automated advising approaches to mediate the challenges of diminishing resources and the perceived lack of value in the conventional approaches for advising (Atalla et al., 2023; Rawatlal, 2022).

In the South African context, academic advising provides structured support by an institutional advisor to a student. The resources necessary to provide such a facility, however, may limit the number of students who can receive such advice. Kuhn (2008, chap. 1) describes various models of academic advising. The nature of the advising could be to inform, suggest, counsel, discipline, coach, mentor and even teach. The practice helps students align their various goals through a continuous developmental process to promote their own success. The act of academic advising lies on an advising–teaching and an advising–counseling spectrum.

Evidence of the positive role by student advisors in student success has been mounting, warranting institutions to formalize and professionalize academic advising. In South Africa, advising is being professionalized through the coordinated efforts of ELETSA, which translates to the word “advising” in Sesotho, which is one of South Africa’s 11 official languages. ELETSA is a South African nonprofit organization that seeks to provide leadership in cultivating collaborations across institutions in the area of academic advising. The association holds allied membership status through the Global Community for Academic Advising (NACADA), which is based in Kansas.

ADVISING AT SCALE

Although wide-scale student advising is thought to significantly improve the graduation rates, traditional forms of advising are relatively resource intensive. While automation and web-based systems are obvious candidates to scale the advising, such systems must offer a high enough level of customization to be effective in the context of a diverse student body. In particular, the operation of such systems should acknowledge a constantly iterative development approach as the needs change in response to the effectiveness or lack thereof of the approaches of the previous iteration.

Advising as a High-Impact Practice

As the practice of academic advising intensifies across institutions, it is being portrayed as a social justice imperative for higher education, and potentially as a high-impact practice (Keup & Young, 2021). However, advising large numbers of students requires substantial investment that challenges under-resourced institutions (Assiri et al., 2020). One-on-one advising approaches alone are therefore neither feasible nor effective, and motivate the inception of automated systems that might minimize incorrect advice and the load on academic advisors (Assiri et al., 2020).

Evidence is now also emerging on the nonacademic or quasi-academic benefits of advising (Haley, 2016). Using expectancy violations theory as a lens, Anderson et al. (2014) argue that student satisfaction with advising is linked to alignment between student expectations of the advising process and perceived advisor behaviors. In some instances, student queries are merely information seeking, such as when they ask for schedules and timetables, financial aid sources, and other pragmatic needs. This is evidenced in the application of chatbots to automate this brokering and to ensure more-effective use of a human advisor's time.

Automated Advising

Recent developments in AI have resulted in the emergence of chatbots in higher education to automate specific student queries for information brokering, thus freeing human advisors to focus on more-complex tasks (Meotti, 2023). AdmitHub, an AI developer, has partnered with more than 100 universities to improve student access and retention by using chatbots (Page & Gehlbach, 2017). Bots of this type use natural language processing to support student success (Chen et al., 2023).

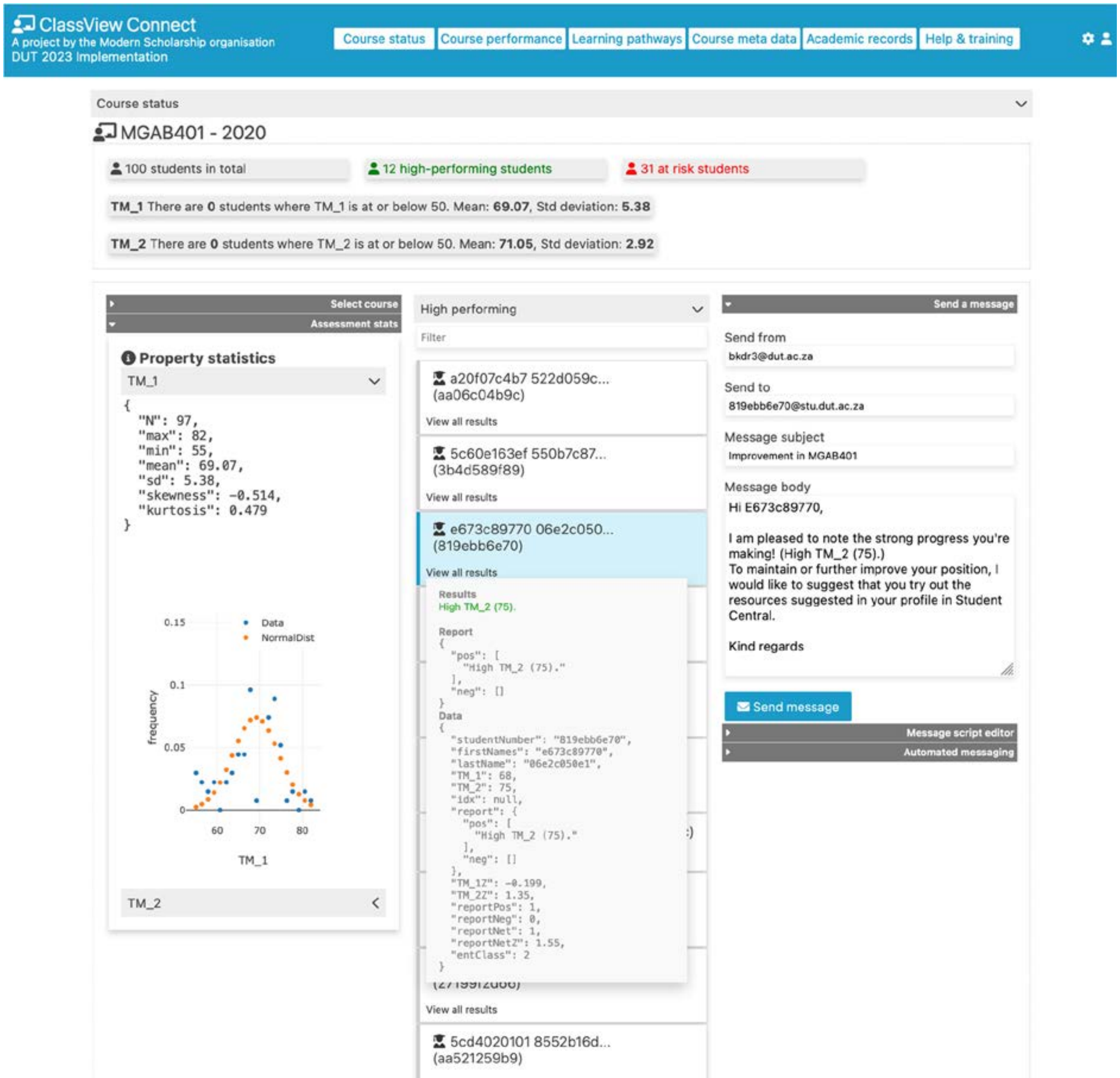
At Georgia State University (GSU), a chatbot helps students with preenrollment processes such as navigating financial aid (Nurshatayeva et al., 2021); GSU's chatbot has led to significant increases in retention and graduation rates. The chatbot's effectiveness continues after enrollment: research indicates that students who used GSU's chatbot were 3% more likely to re-enroll, while having higher rates of FAFSA filing and registration (Nurshatayeva et al., 2021).

Automated systems can aggregate and process large amounts of data more efficiently than humans. This can lead to more-informed advice, since the system can consider various factors and possibilities (Shift, 2022). In recognition of the various roles that support student success, the AutoScholar Advisor system uses AI to generate advice to the various levels of seniority in the higher education institution to fully support and integrate the various interventions that can lead to increased student success.

Evolutions in Student Advising

When generating automated advice to students, we acknowledge that human motivation is a complex field that requires high variance in responses. The factors that prompt action may differ from context to context or from person to person. When generating advice through the AutoScholar Advisor system, it was therefore necessary to evaluate the advice rendered in a variety of contexts to serve as large a group as possible.

A screenshot from an early instance of student advising is shown in Figure 1.

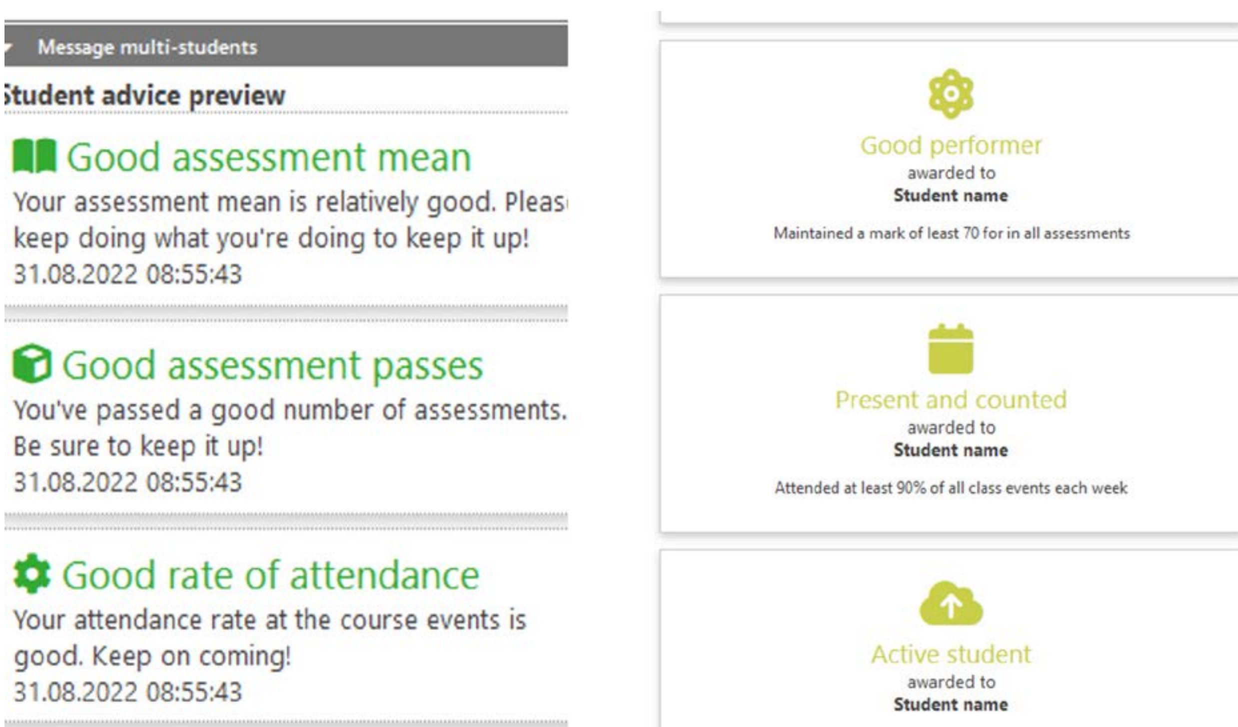


Note: Student numbers and names have been hashed.

In this case, the system calculates the assessment statistics in a class and determines which students are significantly underperforming by computing the number of standard deviations between the mean and each student's result. Based on this value, an apparently personalized message is generated to the student; each message includes some specific data about that student's current and potential future performance. In other words, from a single advising script, which is itself prompted by the student's performance metrics, the system can generate a message to each student that appears to be customized to that student's profile. A default advising script is included that may be further customized by a lecturer or student advisor. The system advises both high-performing students and average-performing students to continue improving and suggests engagement with learning resources available elsewhere in AutoScholar. In the case of underperforming or at-risk students, it further suggests engaging with student support. This form of advising is already a partial evolution; in the first versions, it was possible for the system to alert students of their being at risk of failure. In the version shown in Figure 1, the advice is heavily moderated only to suggest engagement with available services.

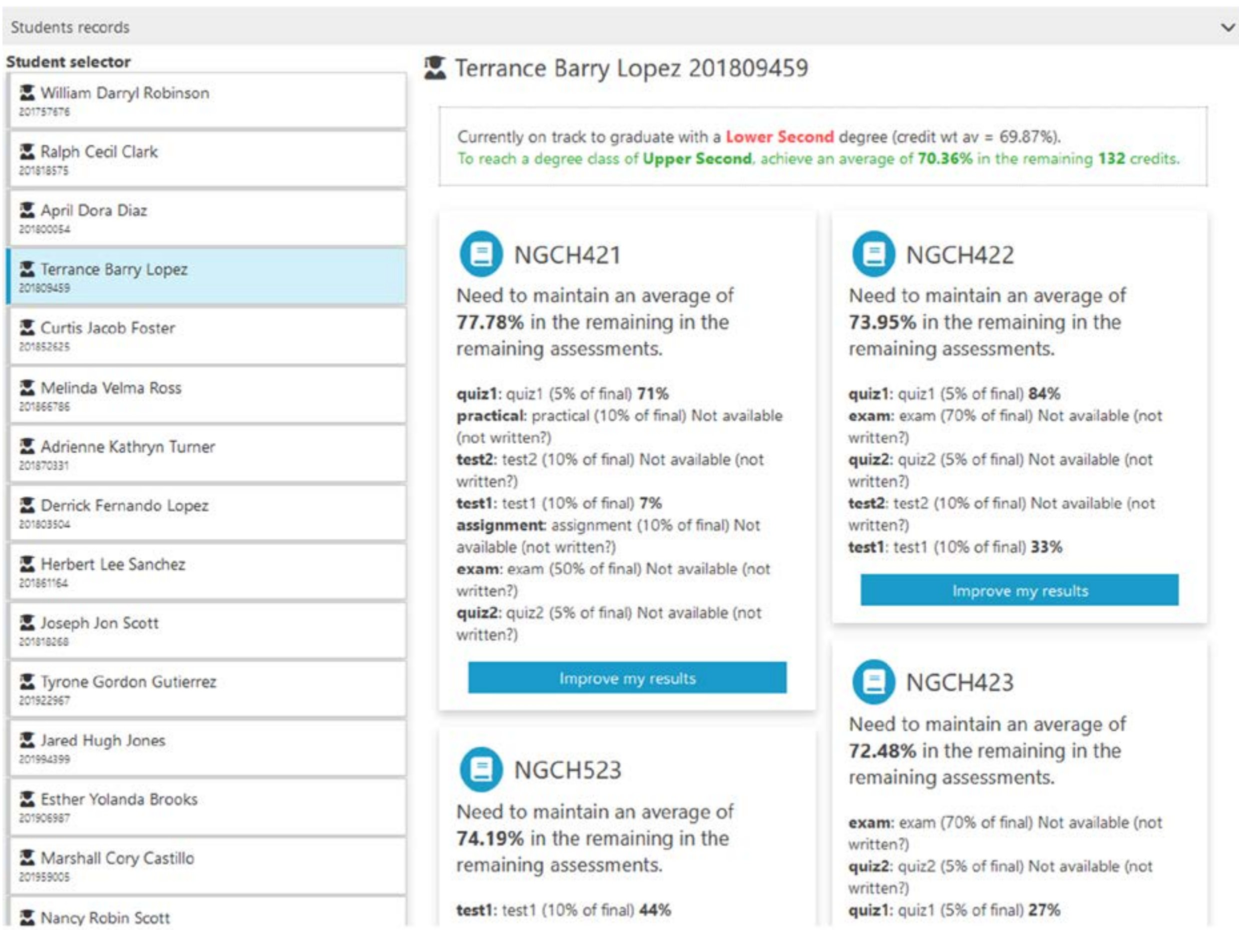
The advising concept may be further generalized to include gamification elements. As shown in Figure 2, the advising may take the form of virtual awards and badges that can be attached to a student's profile. Although these virtual awards require no resources from the institution, they are a powerful means of driving student activity, since students value these awards to a high degree in their applications for scholarships and employment.

Figure 2. Advising in the Form of Virtual Awards



While the application of points, badges, and leaderboards can drive students' level of engagement, one has to apply these methods judiciously to avoid degradation of the educational experience to one of jumping through a series of hoops and thereby limiting the experience of a cohesive curriculum. To develop the sense of an integrated whole, the third evolution of student advising involves providing a large goal to students based on an assumption of a graduation and an assumption that each student is striving not merely to pass, but also to accomplish academic excellence. Figure 3 illustrates this evolution.

Figure 3. Advising for Success ng: The Simulated Case Study



In this case, the system advises students (see top right) of their current status, which, based on their current records, indicates that they are on track to graduate with a lower second class of degree. (For institutions that do not implement such a classification, this can be substituted with mark ranges such as credited weight average in excess of 70%.) The system also alerts students that they can graduate with an upper second class of degree instead by improving their performance by only a few fractions of a percentage point. This provides a student with an overall objective based on an assumption of a final graduation rather than simply the avoidance of failure.

Furthermore, below that top-right box the system shows students which classes they are currently registered for, together with their performance in the various assessments. It notes to students what their minimum performance level should be in the remaining assessments in that class to accomplish the overall goal with respect to the final degree. This evolution of advising can encourage the student to constantly strive higher and achieve a greater level of academic accomplishment.

MULTIDIMENSIONAL ADVISING: ROLE PLAYERS IN HIGHER EDUCATION

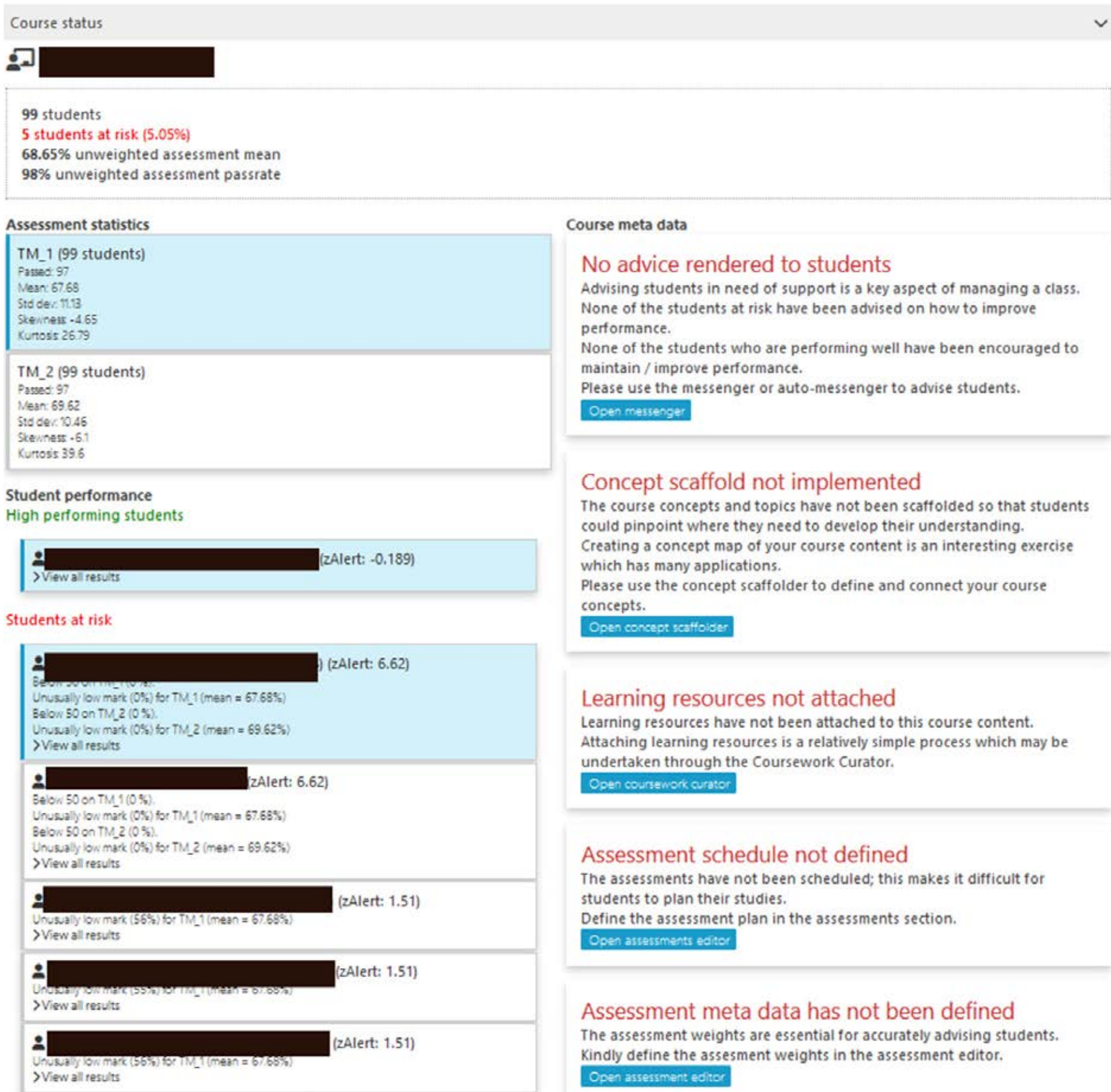
To achieve significant improvements in the progression and hence the graduation rates, it is necessary for the various role players to receive accurate advice. At the student scale, advice on coursework registration as well as day-to-day study habits are a direct influence. Advice to lecturers with respect to students at risk and course management practices can significantly improve the student (and lecturer) experience. At the counselor scale, the ability to benchmark a student against the student population is key. At the executive scale, the allocation of resources to support teaching and learning to specific programs should correlate with the performance levels in the programs.

Role Players in Higher Education: Another Dimension in Advising at Scale

Although advising at-risk students is emphasized at most institutions, it is also necessary to advise the other role players that influence student success. Lecturers require advice on their course/module management, student advisors require insights into student performance to render advice effectively, faculty management require insights into which academic programs require more teaching resources, and executives require insight to the faculties that would benefit from additional financial resources. Some case studies in advising these roles players are shown in Figures 4 through 8.

In Figure 4 it is possible to understand which students require advising as well as to identify the various activities that can be undertaken to better organize the learning content and to generally support better student engagement with the course content.

Figure 4. Screenshot from ClassView Connect Component of the AutoScholar Advisor System



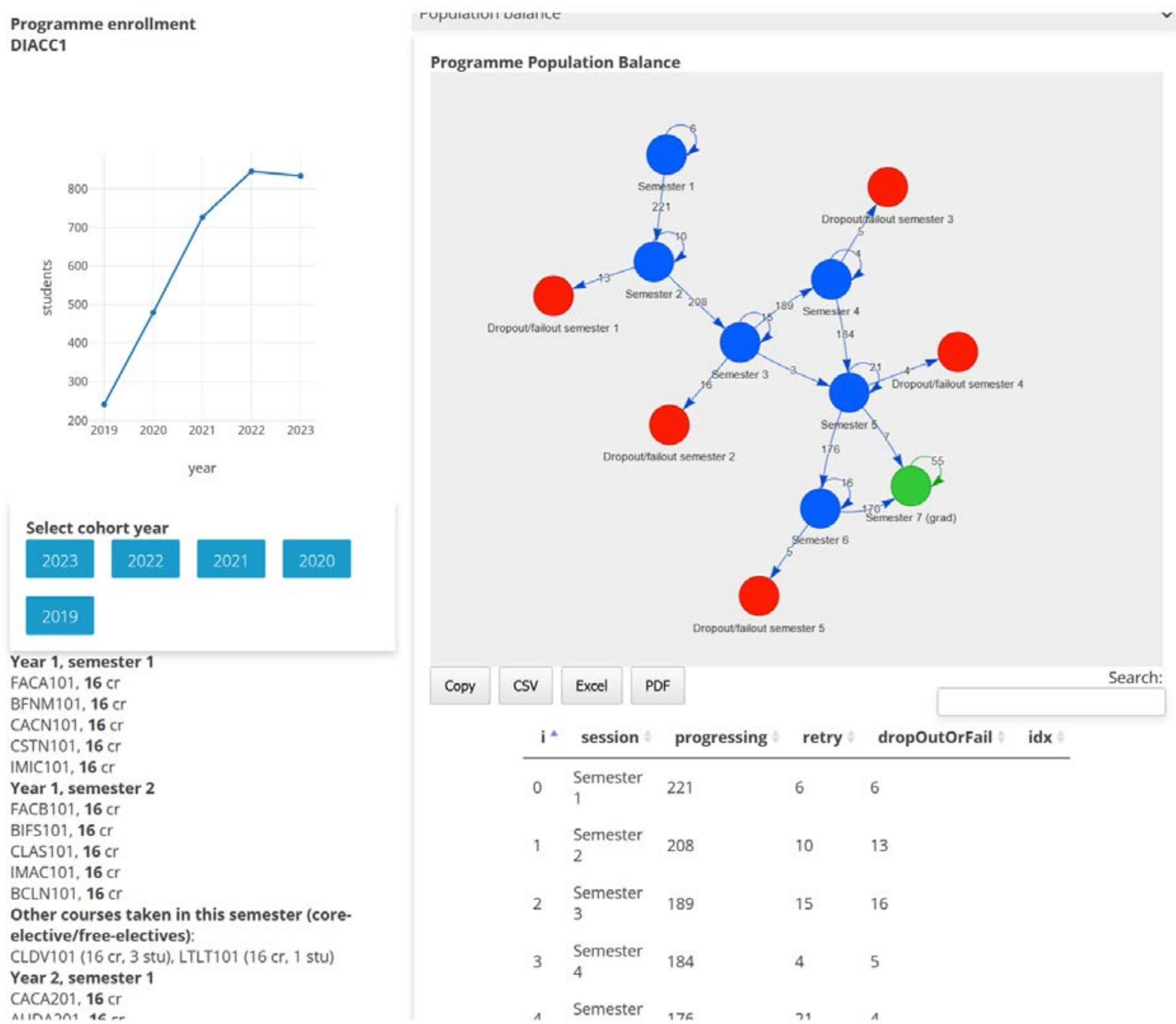
Note: Advice rendered to lecturers to manage classes better.

From the perspective of an academic program manager, such as a head of department or program convenor, it is also useful to identify which coursework in a program should be prioritized to resolve low pass rates. Figure 5 illustrates analysis of an academic program where low pass rates, the influence of a high confluence of prerequisite requirements, and the impact on senior courses; students then take those courses later than intended.

Figure 5. Program Analyst Component of AutoScholar: Identification of Coursework Issues

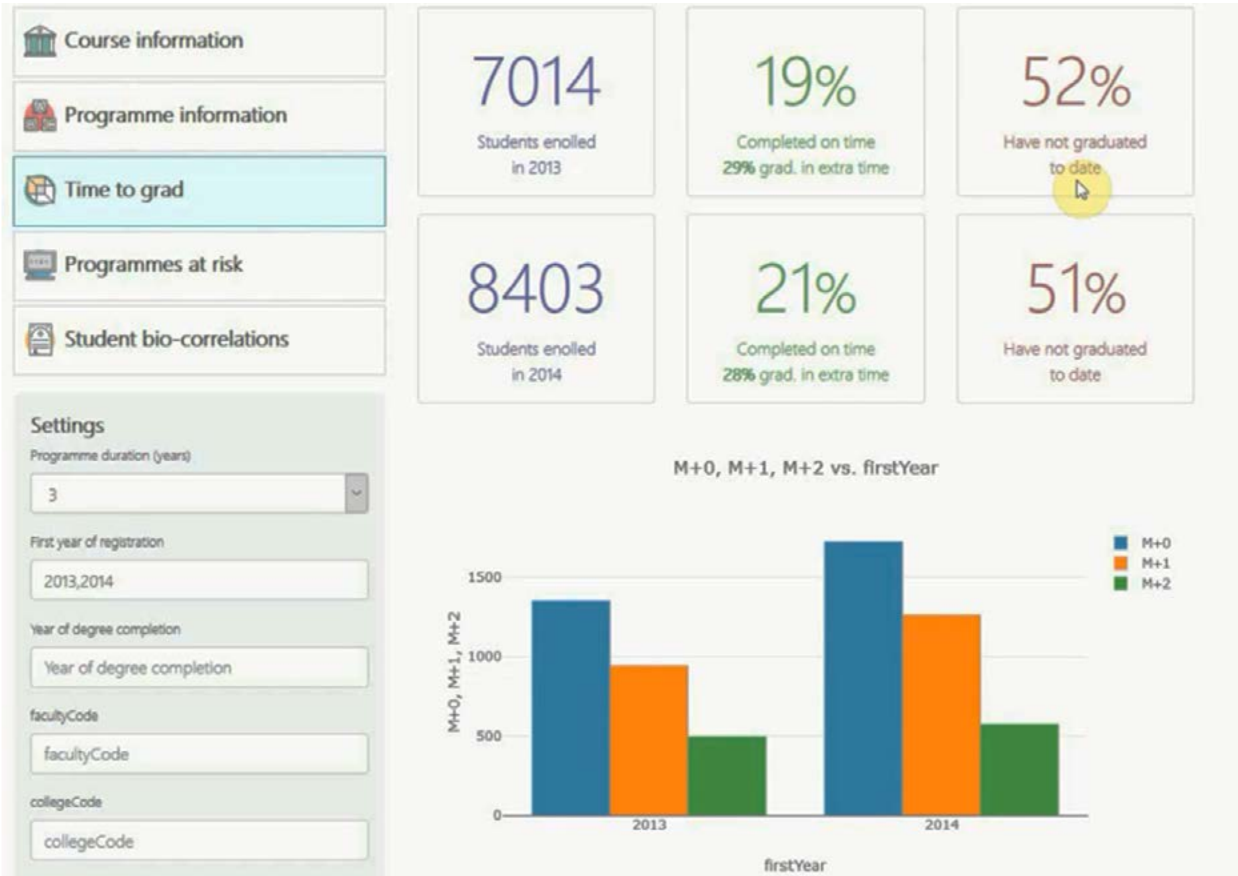
To fully advise faculty staff on student progression, it is also necessary to evaluate the transfer of students from one semester to the next, and to maintain awareness of the various combinations of courses involved in the various routes to graduation. Figure 6 illustrates that a program manage can determine at which point in the curriculum the largest number of students exit or recycle.

Figure 6. Population Balance Illustrating Student Progression through an Academic Program



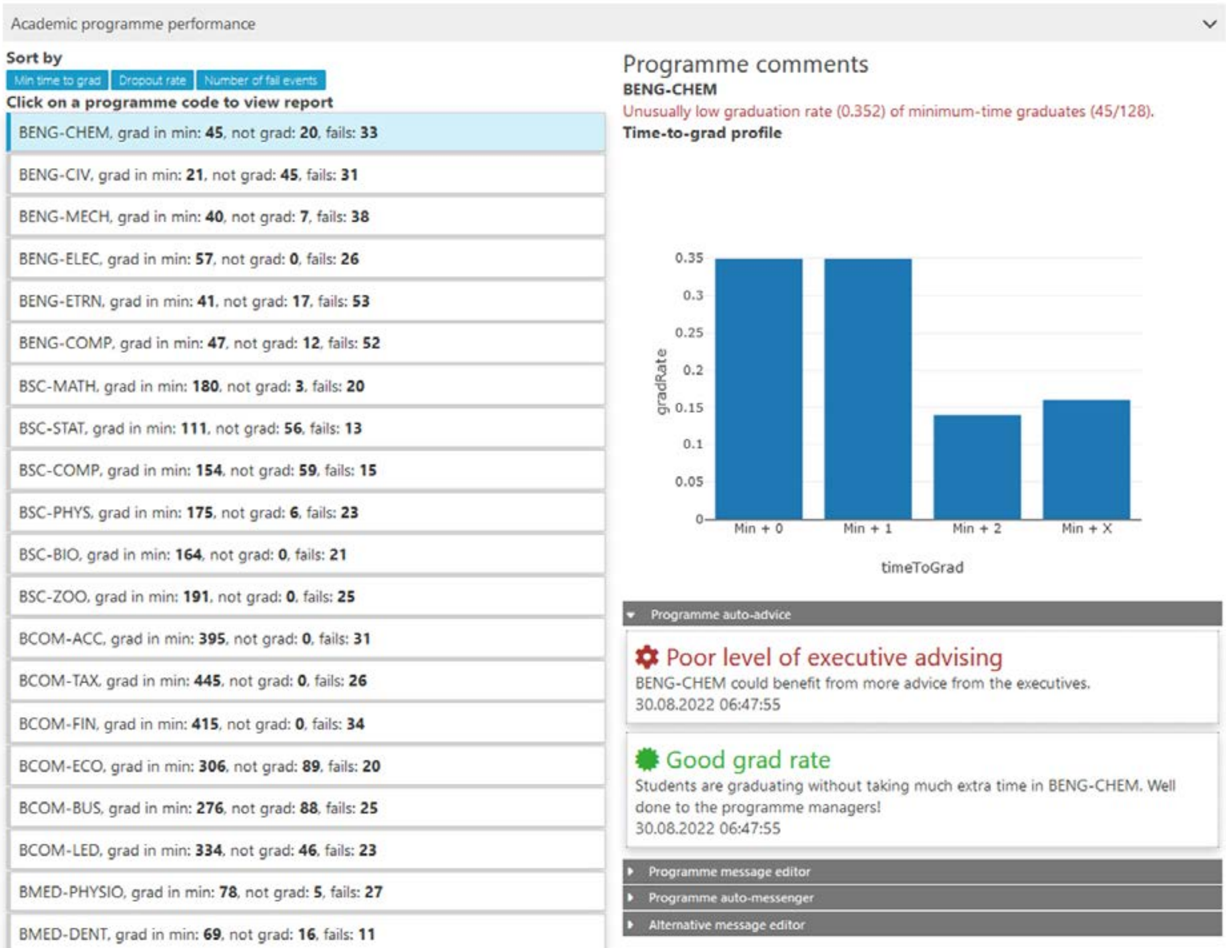
At the whole-institution scale, executives maintain a bird's-eye view of the entry and graduation statistics. In particular, given an entering cohort in a particular year, it is necessary to monitor what fraction of students complete in minimum time and what fraction exit without graduating (Figure 7).

Figure 7. Executive Insight Component of AutoScholar Advisor System to Monitor Institutional Progression



To take action by alerting relevant staff or allocating resources, the next step would be to determine, among all academic programs at the institution, which programs exhibit the lowest pass rates and lowest performance indices. Figure 8 illustrates that such programs can easily be identified.

Figure 8. Executive Insight: Identifying Academic Programs in Need of Support



It is therefore possible for all role players in higher education to receive sufficient insight and hence to apply suitable interventions or allocate resources to ameliorate the limitations identified. Such data-oriented advising may be directly applied in most cases. At the student level, however, it could be more necessary to moderate the advice rendered by interpreting the results and suggesting interventions based on the student temperament and degree of reception to critical feedback.

Hybrid Advising

In academic advising, human advisors often do not have all the requisite information at hand, with inherent limitations in what they can do with such information. For example, an advisor cannot make decisions for an advisee, but can provide various alternatives for the student to consider. Similarly, an advisor cannot increase the native ability of the advisee, but can encourage maximum use of that ability. Advisors also cannot reduce an underperforming student's academic load, but can recommend appropriate interventions. Confidential matters also present challenges, since advisors must balance the need for information exchange with the need to respect student confidentiality. Furthermore, when complex problems arise related to financial aid, mental or physical health, or personal or social counseling, advisors often have to refer students to other professionals.

Given the inherent diversity in student attributes, moderating advice to students is essential as students navigate the complexities of their institutions. Personalized connections can help bridge the gap between expectations and experiences, especially for international students and those who require support to prevent departure before graduation (Moore, 2022).

This points to the value of hybrid advising, which combines in-person and online elements, and can help to mitigate some of these challenges by using chatbots to handle routine transactions while leveraging human interactions to address specific and unique situations. The Covid-19 pandemic accelerated the blending of in-person and online learning in many schools, a shift that, despite its challenges, can potentially enhance the academic experience in the long run. This hybrid model can help break down barriers to access, allowing universities to reach a broader and more diverse population of students. It can also better meet the changing workforce's needs and provide working adults with lifelong learning and career opportunities (Selingo & Clark, 2021).

Implications for Institutional Research

The approaches outlined here emphasize awareness of a need for intervention at a specific point of application. It is also possible to apply this approach to evaluate the effectiveness of any specific interventions that might be applied. Such an approach is typical of Improvement Science frameworks (Perry et al., 2020), where the continuation of an intervention must be evaluated according to the observed improvement or lack thereof. In fact, it is a well-established practice in Improvement Science to reevaluate not only the suitability of any applied interventions, but also the metrics used in the evaluation itself.

It is also worth noting that, although metrics are cited for the performance of students at the whole-institution scale, the system also generates the same statistics at the college, faculty, and academic program levels. This is significant since the context of the student and nature of studies undertaken will influence the performance metrics. It then becomes possible to customize the applied interventions rather than assuming that a blanket strategy applies to all disciplines.

The ease of access to data analysis may also afford new insights to the student support staff. Student advisors often complain that their role devolves to simple information brokering rather than affording students insight to performance improvement. This is at least in part due to nonacademic advising emphasizing the student impression of the severity of the challenges faced. If an advisor is also able to correlate this with actual changes in performance as reflected by data showing a student's progression, it might be possible to review perceived challenges more objectively and hence to raise the value of the advice rendered.

It is still necessary to actively challenge the interpretation of data, however. Various forms of bias easily enter even careful analysis, to say nothing of the tendency to adopt an auto-generated message as the gospel truth. There are as many as six main categories of bias (confirmation, selection, historical, survivorship, availability, and outlier). Without suitable training, it is all too easy for a viewer to take action that yields unexpected results.

On the other hand, it is known that the students most in need of support are often the least likely to ask for it. Automation may play a role in provoking at least a conversation if not an active engagement between a student and a human advisor that might not otherwise have occurred. There are rich possibilities for the hybridization of automated and human advising.

There are other implications for the AutoScholar Advisor system for institutional research (IR) and institutional effectiveness (IE) professionals. It is possible that IR or IE officials can engage in collaborative work with academic advising staff on how data are collected, managed, and prepared for the feedback loops. In addition, the IR analysts might want to design a study to examine student success based on use of the AutoScholar Advisor system (e.g., perhaps a pre–post type of research design). This could yield great benefits for students and provide return-on-investment rationale for use of the system. Other research studies may also be considered, such as the evaluation of different models of advising on student experience and satisfaction: automated, human, and hybrid advising.

IR and IE officials might also want to ensure that other colleagues are considering potential bias that can occur in data (majority vs. minority students, or other known facets of differences). Indeed, we believe that this system can help underserved student populations and that IR officials can help articulate those benefits to campus colleagues.

CONCLUSION

In this article we have attempted to demonstrate that, while academic advising has consistently been rated a top predictor of students' success and satisfaction during their undergraduate careers (Anderson et al., 2014), the traditional human-centered academic advising is a resource-intensive process that is difficult to sustain, prompting institutions to develop alternative advising models. Based on our experiences of advising development at a South African university, we contend that automated systems that use AI techniques (such as the AutoScholar Advisor system) can "minimize incorrect advice, minimize the load on academic advisors, solve the issue of the limited number of advisors, and free up more of their time" (Assiri et al., 2020, p. 1).

However, automated systems alone can have unintended consequences, such as engendering demotivation among students. We therefore conclude with the proposition that the optimal approach to advising is a hybrid between human intervention and automation, where the automation augments human judgment. In this modality, the automated advice function provides the initial prompt to alert students of their at-risk status or of their potential to attain higher grades. These students are then ushered to appropriately qualified advisors who provide the human touch to ameliorate the limitations of automated systems.

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