A Peer in the Loop: The Human Touch that Analytics Needs

Jenna Matthews[1,2], Hillary Swanson[1], Morgan Slugantz[3], Kausha Miller[3]
[1]Utah State University, [2]Pearson Education, [3]Bluegrass Community & Technical College
jenna.matthews@pearson.com, hillary.swanson@usu.edu, mslugantz0004@kctcs.edu, kausha.miller@kctcs.edu

ABSTRACT: Efforts to put humans in the analytics loop focus on getting instructor feedback and perspectives. While this is beneficial, there's a human touch that is lacking from both the interpretation and use of learning analytics insights. We discuss the process of identifying a new behavioral metric and involving the voice of a peer in the interpretation and (most importantly) use of the metric for student support. We show preliminary results indicating that both the new metric and peer voice contributed to improved success in a general education math course.

Keywords: Peer mentoring; community college; mathematics; reengagement

1 MOVING FROM A GOAL TO A METRIC

As a group, students attending community college are among those most in need of support. They can be especially isolated, making the connection with peers increasingly important as they often lack the on-campus support of residential students (Crisp, 2010). For older, non-traditional students, difficulty in key courses such as Math, combined with a lack of support and sense of community can lead to withdrawal from school (Bahr et al., 2022). In recent research, Guo et al. pointed out that frequently the withdrawal is not tied to cognitive difficulties, but rather to affective elements, such as relationships with other individuals at the institution, personal factors (such as self-efficacy and mindset), and academic support (2022).

1.1 The Context

This paper reports on work taking place within a long-term research-practice partnership involving a community college in the southeastern United States. The goal of the partnership was to improve student success within a general education mathematics course. This course had historically poor completion rates - made worse by the COVID-19 pandemic - and was required for students completing non-STEM degrees. In many instances, this course stood between students and graduation.

Earlier work had included a variety of efforts - including a partial redesign of the course - without achieving the desired results. So, as a team, we returned to raw activity data to find something which could be a useful early indicator of problems.

Part of the course design involved students working on math problems in an online learning environment. Students were able to work on assignments and quizzes with flexibility - and could stop and return later if needed. Data collected in this environment included a variety of student actions - such as checking their answer, asking for a hint, or working through a guided solution - as well as flags to indicate whether the student got a specific answer correct.

1.1.1 Defining "Giving Up"

Using these actions captured in the online environment, we created a metric called "Giving Up" using the following process:

- We started by grouping all student activity into sessions, using the Google Analytics (Google) standard window of 30 minutes of inactivity to split working time into working sessions.
- Within a session, we identified each problem with which the student interacted. These interactions could include checking their answer, asking for a hint, or working through a guided solution. In order to capture those problems where students were working, not just looking (a single interaction), we limited the data set to those problems with multiple interactions.
- Using the problems with which the students interacted from step #2 as the denominator and the number of solved problems as the numerator, we came up with a percentage of problems which were solved. The inverse of solved problems represents those with which students interacted, but which they did not solve before ending their session. That inverse was the session-level "Giving Up" percentage.

In this way, we had a percentage score which could be tracked across time, allowing us to see both fluctuations (where a score would alternate between climbing and falling) and trends (where a score would change in the same direction – climbing or falling – across several sessions).

We reviewed previous semesters of the course using this metric and saw significant differences between successful (A/B/C grades) and failing (D/F/W grades) students in terms of their average change between sessions – whether a subsequent session had a higher, lower, or unchanged "Giving Up" percentage.

We also reviewed the "Giving Up" behavior over time for students who ultimately withdrew from the course. We found that individual sessions with high rates of "Giving Up" were unimportant - and nearly universal. Fluctuations from one session to the next were too noisy to be useful for flagging students in need of support. However, a trend of increased "Giving Up" across three sessions worked as an early indicator – giving support staff weeks of time before students withdrew from the course. Based on these findings, we used this trend as a flag for student outreach.

2 A PEER IN THE LOOP

For the semester, we focused on a single course on a traditional 16-week schedule with a total of 267 students. No other changes were made to either the course content or delivery during the semester.

In previous research covering a range of both ages and disciplines, mentorship by near-peer mentors - fellow students who have slightly more experience or knowledge - has been shown to be a sustainable option for improving student engagement, interest, and academic outcomes (Clarke-Midura et al., 2018; Pluth et al., 2015; Tenenbaum et al., 2014). This research provided our rationale for including a peer guide on the project team, and more importantly having the peer guide conduct the outreach. Our project team included a researcher/data scientist, an assistant dean/coordinator at the college campus, and a peer guide - a student employee at that college campus who met with our team weekly and handled the student outreach. For both the data scientist and coordinator, this project was part of their regular work, requiring no additional funding. During weekly meetings, the researcher would present/explain data and the instructor would lead the prioritization process and give the “teacher version” of an outreach message for students.

The peer guide participated in the meetings, gave feedback on the metrics, did the message translation (going from a “teacher voice” to a “student voice”), and conducted the actual student outreach. During the week, the peer guide reached out to students via email, text, and phone. While there was some prioritization of methods based on the severity of need, the peer guide was encouraged to adapt the mode, method, and message as preferred. Outreach to students was very open-ended, offering support to help students re-engage and finish the course successfully.

3 REVIEW & RESULTS

At the end of the semester, we reviewed data for outreach, activity, and outcomes. During the semester, 159 distinct students received a total of 331 outreach messages. Even though most students never responded, we did see an impact in both individual student behavior and course success rates related to the outreach. Individual student behavior, measured as a reduction in “Giving Up” (or working on problems but leaving them unsolved) for the session after outreach, was especially meaningful for several student groups as shown in Table 1 below.

Table 1: Reduction in “Giving Up” behavior – average percentage change in subsequent session.

	Post-Outreach Records			Not Post-Outreach Records			
Group	Improvement	Students	Records	Improvement	Students	Records	p-value
First-Generation	6.01%	46	72	0.91%	108	5059	0.1314
African American	7.83%	14	33	-1.00%	37	1755	<0.0001***
Pell-Eligible	8.09%	83	132	0.96%	186	8573	0.0091***

We also saw a large improvement in the course-wide success rate (% of students receiving an A/B/C grade in the course) as shown in Table 2 below:

Table 2: Difference in course success rates.

Category	Fall 2019	Fall 2020	Fall 2021
Students	201	242	267
Success Rate	45.27%	37.19%	46.07%
Change Year-over-Year		-8.08%	+8.88%

The success rate for Fall 2021 – the semester during which we ran this project – put this course slightly above their pre-COVID numbers. These results led to an expansion of the work with additional courses and campuses joining the ongoing project.

4 DISCUSSION

As in previous learning analytics studies we are tracking a behavior ("Giving Up") rather than performance or outcomes, to identify students who may need help. It is a behavior which was defined as part of ongoing research-practice partnerships, and which has not before been available to faculty, advisors, or other members of the student support teams.

Perhaps more importantly, however, is that the outreach based on this behavior is coming from a peer, in a student voice. We have seen results which suggest that peer outreach may have some of the same benefits as those already identified in peer mentoring (Clarke-Midura et al., 2018; Pluth et al., 2015; Tenenbaum et al., 2014). Not only was the peer guide able to translate from a teacher to a student voice, but the outreach was open-ended. One of the things we found during our pilot was that students' struggle was not necessarily academic but frequently related to their life outside of school, including issues related to employment, illness, or family problems. In these instances especially, arbitrarily sending students to a tutor would not have been helpful because it wasn't the math causing the problems.

We have since expanded the usage of this metric to additional courses and campuses where we are continuing to see similar improvements in behavior and course outcomes. Ongoing and planned analysis includes understanding the impact of different methods of student contact, comparing behavior across a larger time frame, and identifying the most effective window for peer outreach.

REFERENCES

Bahr, P. R., Boeck, C. A., & Cummins, P. A. (2022). Is Age Just a Number? A Statewide Investigation of Community College Students' Age, Classroom Context, and Course Outcomes in College Math and English. *Research in Higher Education*, *63*(4), 631–671. https://doi.org/10.1007/s11162-021-09660-w

Clarke-Midura, J., Poole, F., Pantic, K., Hamilton, M., Sun, C., & Allan, V. (2018). How Near Peer Mentoring Affects Middle School Mentees. *Proceedings of the 49th ACM Technical Symposium on Computer Science Education*, 664–669. https://doi.org/10.1145/3159450.3159525

Crisp, G. (2010). The impact of mentoring on the success of community college students. *The Review of Higher Education*, *34*(1), 39–60.

Google. (n.d.). *How a web session is defined in Universal Analytics*. Google Support. https://support.google.com/analytics/answer/2731565?hl=en#zippy=%2Cin-this-article.

Guo, Y., O'Halloran, K. P., Eaker, R. M., Anfuso, C. L., Kirberger, M., & Gluick, T. (2022). Affective Elements of the Student Experience That Contribute to Withdrawal Rates in the General Chemistry Sequence: A Multimethod Study. *Journal of Chemical Education*, *99*(6), 2217–2230. https://doi.org/10.1021/acs.jchemed.1c01227

Pluth, M. D., Boettcher, S. W., Nazin, G. V., Greenaway, A. L., & Hartle, M. D. (2015). Collaboration and Near-Peer Mentoring as a Platform for Sustainable Science Education Outreach. *Journal of Chemical Education*, *92*(4), 625–630. https://doi.org/10.1021/ed500377m

Tenenbaum, L. S., Anderson, M. K., Jett, M., & Yourick, D. L. (2014). An Innovative Near-Peer Mentoring Model for Undergraduate and Secondary Students: STEM Focus. *Innovative Higher Education*, *39*(5), 375–385. https://doi.org/10.1007/s10755-014-9286-3