CHAPTER 4.

LEARNING ANALYTICS IN WRITING INSTRUCTION: IMPLICATIONS FOR WRITING ACROSS THE CURRICULUM

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Learning analytics tools process data collected from instructional applications and learning systems to estimate the likelihood of student success in a given course or program of study and to identify points at which interventions might increase the likelihood of student success. They can also be used to carry out retrospective analysis of student success for course redesign. While these tools are widely used in many disciplines in higher education, their adoption in writing and writing-intensive courses has been slow. Nonetheless, a subset of learning analytics tools, characterized as writing analytics tools, have seen growing use in the field of writing studies. This chapter explores the uses of learning analytics tools and writing analytics tools within composition and writing across the curriculum, considers concerns about their use in instructional contexts, and discusses factors likely to shape their adoption and use.

Learning analytics—the analysis of data drawn from a wide range of sources including learning management systems, adaptive quiz tools, student information systems, and communication tools, among others—has been a growing area of discussion and concern among faculty across the curriculum (Daniel, 2015; Fournier et al., 2011; Siemens & Long, 2011; Viberg et al., 2018). While the use of data to gain insights into student learning performance has long been a common practice in educational research, improvements in our ability to assemble and analyze large sets of data from learning tools and communication tools promise to enhance our ability to understand how various learning behaviors, instructional practices, and instructional material shape student success in our courses.

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The primary purposes for which learning analytics data and tools are used include

- identifying students who may be in danger of failing or performing poorly in a course while the course is being offered
- predicting the likelihood of success of students prior to the start of a course
- identifying learning behaviors that are correlated with student success (or the lack thereof) in a course (typically after the course has been completed)
- identifying course materials and assignments that are correlated with student success (or, again, the lack thereof)

The findings from these kinds of analyses can be used to understand patterns of student performance in a course after it has been offered, typically with the goal of modifying or substantially redesigning a course. They can also be used to understand the differential impact of new assignments, learning materials, and assessments on students during and after the academic term in which a course is offered. Learners can benefit from the reports generated by learning analytics tools, both by gaining a sense of their progress in a course and by obtaining information about activities they might engage in to advance their progress. For example, a student who is struggling in a writing or writing-intensive course might be given advice regarding resources, such as writing centers or relevant digital learning materials, that they could make use of while the course is in progress.

In writing-across-the-curriculum (WAC) courses, the data made available through learning analytics tools have the potential to help program leaders and instructors understand the differential impact of particular instructional methods and materials in a course. For example, data about student behaviors as they worked on a staged writing assignment—one, for instance, that involved a topic proposal, a review of literature, contributions to web discussion forums, a research plan, and multiple drafts—would support analysis of the relative success of students who engaged at higher or lower levels (or did not engage at all) during various stages of the assignment. Those data might also allow comparison of behaviors across writing assignments and, in turn, those behaviors might be considered in light of particular instructional practices employed before or during work on assignments. In addition, the data might allow comparison of both the behaviors and success across groups of students, such as majors and non-majors, upper-division and lower-division students, and students from various demographic groups. In turn, this data could be used to assess the overall impact of the WAC program on student learning and success at the institution.

Learning analytics tools are increasingly included in digital learning applications and platforms. Learning management systems such as Canvas and Blackboard, for example, allow instructors to view a basic but nonetheless informative set of learning analytics reports, some of which allow customization. Among other information, instructors can view completion of assignments, logins, scores on quizzes and exams, and activity on discussion forums. Similarly, the learning analytics tools built into learning systems offered by textbook publishers, such as McGraw-Hill's Connect and Macmillan's Achieve platforms, support the analysis of student learning behaviors, typically with the goal of identifying students who might benefit from intervention by the instructor. More powerful learning analytics systems, such as Barnes and Noble Education's LoudSight, provide predictive analyses based on course performance data, student demographic information, and student performance in past courses. These systems offer customizable reports, support one-to-one and one-to-many messaging between instructors and students, and can send automatic "nudges" (brief messages delivered through email or text messaging) to students whose behavior (or lack of behavior, such as failing to complete assignments or neglecting to log in regularly to a learning management system) suggests that they are in danger of performing poorly in the course.

In addition to these types of learning analytics tools, a related set of tools—such as EAB's Navigate—are being used to help institutions identify courses in which students struggle and, perhaps more importantly, to reveal course combinations within an academic term or course sequences across academic terms that appear to be correlated with lack of success.

The growing sophistication and predictive accuracy of these analytics tools have allowed instructors to become aware of and intervene to address student behaviors that undermine learning and success. In some cases, institutions have used this information during course redesign to inform efforts to improve teaching effectiveness, student learning, and student success. For WAC leaders, it is difficult to overstate the importance of learning analytics data and the uses to which such data can be put in pursuing the goals of a WAC program. On a purely instructional basis, these data can be used to identify courses that might benefit from the use of writing-to-learn, writing-to-engage, and writing-to-communicate assignments; to assess the effectiveness of those assignments; and to determine whether to continue to use them and, if so, how they might be enhanced. On a more pragmatic programmatic level, these data can also play an important role in determining institutional funding priorities and, consequently, can shape decisions about continuing and enhancing institutional support for WAC initiatives.

SOURCES OF LEARNING ANALYTICS DATA

Learning analytics data are related primarily to the behavior, products, and performance of students within a course. This can include data drawn from

- learning management systems, such as logins, access to files, and quiz tools and discussion forums, among other tools (Daniel, 2015; Zhang et al., 2018)
- eReaders, video players, and other tools for accessing and interacting with course content (Junco & Clem, 2015; Shoufan, 2018)
- learning tools provided by vendors and publishers, such as adaptive quiz tools and interactive exercises (Lewkow et al., 2015)
- "multimodal" data sources, which can reveal student location and other activities in real time, such as posting to social media and accessing wireless networks, by drawing on data from the Internet of Things, cloud data storage, and wearable technologies (Di Mitri et al., 2018)
- writing carried out in formal and informal assignments, including journaling and posts on discussion forums (McNely et al., 2012; Shum et al., 2016; Wise et al., 2013; Yu et al., 2018)

These data are often analyzed in combination with academic information, such as scores on college entrance examinations and performance in high schools, as well as demographic information drawn from a student information system, such as race, ethnicity, gender, and family income. In some cases, learning analytics data from a specific course will be analyzed in combination with data about student participation in institutionally supported activities, such as attending tutoring and study group sessions and meeting with faculty and academic advisors. In rare cases, these data might also be considered in light of activity on social networks and location data that might be derived from connections to a campus network or access to mobile phone data.

LEARNING ANALYTICS DATA AND TOOLS: PRACTICAL AND ETHICAL CONCERNS

While recognizing the insights afforded by the use of learning analytics tools, a number of scholars have called attention to the potential misuse of information they produce. Slade and Paul Prinsloo (2013), for example, observed that predictions about the likelihood of successful course completion could lead instructors and advisors to discourage students from taking courses or pursuing programs of study in which they are likely (but by no means guaranteed) to fail. Their caution is particularly important given the difficulty faced by students—often first-generation college students and/or members of historically underrepresented groups—who might enter higher education courses with comparatively lower levels of academic preparation than students who are members of majority group, whose families enjoy higher socio-economic status, or whose families include members with college degrees. Slade and Prinsloo also expressed concern that inappropriate conclusions might be drawn about the teaching effectiveness of faculty members, a concern that echoes arguments made by a number of scholars about the reductive nature of student evaluations of teaching (see, for example, the 2017 meta-analysis by Uttl et al., 2017). Other scholars have argued that learning analytics tools are too immature to be used without a great deal of caution, citing privacy concerns (Jones & Salo, 2018; Pardo & Siemens, 2014), reservations about issues related to privacy and the potential commercialization of student data (Flavin, 2016; Rubel & Jones, 2016), and concerns about the reductivism inherent in any analysis of "big data" (Stephens, 2017).

The importance of these concerns for scholars involved with learning analytics are addressed in the editor's introduction to a recent issue of *The Journal of Learning Analytics*:

> Questions related to privacy and ethics in connection to learning analytics have been an ongoing concern since the early days of learning analytics. Examples of some of the major questions are related to the ownership and protection of personal data, data sharing and access, ethical use of data, and ethical implications of the use of learning analytics in education. It is well recognized that these issues lie at the very heart of the field and that great care must be taken in order to assure trust building with stakeholders that are involved in and affected by the use of learning analytics. (Gašević et al., 2016, p. 2)

With these concerns in mind, numerous proposals have been made regarding ethical principles and practices related to both the analyses that learning analytics tools produce and access to the data on which they are based. In 2013, George Siemens suggested that we look not only at data ownership and retention but also at the issue of learner control over the uses to which that data should be put. One year later, Abelardo Pardo and Siemens (2014) proposed an ethical framework for learning analytics that focused on four aspects of privacy that had emerged in response to the growing collection of digital user data over the past two decades: "transparency, student control over the data, security, and accountability and assessment" (p. 448). More recently, Andrew Cormack (2016) has argued that we should draw on ethical frameworks used in medical research to separate "the processes of analysis (pattern-finding) and intervention (pattern-matching)" so that we can protect learners and teachers from "inadvertent harm during data analysis" (p. 91). Hendrik Drachsler and Wolfgang

Greller (2016) proposed DELICATE, an eight-point checklist based on recent legal principles and the growing literature on ethical use of learning analytics data that supports a "trusted implementation of learning analytics" (p. 89). And in a promising approach to preserving privacy while ensuring benefits to learners and teachers, Mehmet Emre Gursoy, Ali Inan, Mehmet Ercan Nergiz, and Yucel Saygin (2017) have developed and tested a framework that for the development and enforcement of "privacy-preserving learning analytics (PPLA)" (p. 69).

Building on these efforts, a small but growing number of higher education institutions (e.g., Charles Sturt University, 2015; Colorado State University, 2018; University of Michigan, 2018), professional organizations such as the Society for Learning Analytics Research (Gašević, 2018, personal communication) and the Reinvention Collaborative (Jensen & Roof, 2016), and nongovernmental organizations such as Jisc (Sclater, 2014; Sclater & Bailey, 2015) have developed frameworks to inform the ethical use of learning analytics data and tools. Other institutions and organizations are currently adapting existing or developing new frameworks. While no large breaches of learning analytics data had yet been reported at the time this chapter was completed, it seems almost inevitable that breaches will occur. Similarly, while no reports of harm to students or faculty as a result of using learning analytics tools and data had been made by the time this chapter was completed, sufficient expressions of concern have been made to suggest that some institutions might find evidence of unethical behaviors.

Even as these ethical frameworks have been developed, however, many of the scholars who point to the potential benefits of collecting and analyzing student learning data—including some who have participated in the development of the ethical frameworks—have argued that it is both far too early to draw strong conclusions about the effectiveness of learning analytics tools and data and that we should continue to explore how they might be used effectively and appropriately. These scholars have observed, for example, that the quantitative data provided through learning analytics are used most effectively in combination with qualitative data (Pardo et al., 2015), suggested that students can benefit from "nudges" and other automated communications that might promote self-regulated learning (Howell et al., 2018; Pilgrim et al., 2017), and pointed to promising approaches that can help students use learning analytics to succeed in courses in which they might otherwise struggle (Drachsler & Greller, 2016; Macfadyen et al., 2014).

LEARNING ANALYTICS IN WRITING INSTRUCTION: WRITING ANALYTICS

Within writing studies, the use of learning analytics tools in writing courses and writing-intensive courses has only recently received consistent scholarly attention. As Joe Moxley and Katie Walkup noted in 2016, "Despite a growing interest in the applications of WA [Writing Analytics], and several conferences on these applications, including LAK (Learning Analytics and Knowledge) and EDM (Educational Data Mining), there remain surprisingly few foundational pieces on WA" (p. 1). Indeed, while Moxley (2013) and others had long addressed questions about the role of "big data" in writing research, the term "writing analytics" did not come into use until 2015, when Simon Buckingham Shum (2015), a cognitive psychologist with a strong interest in learning analytics, coined the term. By 2016, Shum et al. had defined writing analytics as "the measurement and analysis of written texts for the purpose of understanding writing processes and products, in their educational contexts, and improving the teaching and learning of writing" (p. 481).

Since 2016, Shum has conducted a series of workshops on writing analytics at the annual Learning Analytics and Knowledge conference, which is sponsored by the Society for Learning Analytics Research (SoLAR). Shum, who has focused largely on reflective writing, has shown a strong interest in the use of automated scoring of texts within specific pedagogical contexts. His work is informed largely by work in latent semantic analysis, corpus linguistics, and cognitive psychology. It does not appear to be informed in any meaningful way by work in the field of writing studies.

The limited attention paid by writing and WAC scholars to learning analytics (and, more recently, writing analytics) does not reflect a reluctance to use data to inform decisions. For decades, these scholars have drawn on the kind of data now being used in learning analytics both to carry out WAC program evaluations and as sources of information in scholarly work. In the 1980s, for example, Art Young and Toby Fulwiler (1986) and their colleagues at Michigan Tech University drew heavily on institutional and student data, such as course completion data, grades, and graduation rates, as well as analysis of student writing, to inform their comprehensive evaluation of the first five years of Michigan Tech's WAC program. Similarly, in an effort that significantly predates the development of predictive analytics tools, many first-year-writing programs have relied on student performance data—such as high school GPA and class rank as well as scores on the verbal portions of the SAT and ACT examinations—to place students into or exempt them from introductory composition courses. More recently, Eodice, Geller, and Lerner (this volume) have employed a range of data collection and analysis methods to explore and attempt to understand what students and faculty members bring to their work as writers. And importantly, corpus linguistics and content analysis, which can be used to search for patterns in large collections of texts, have long played important roles in the study of student writing (see, for example, Carley & Palmquist, 1992; Palmquist, 1990, 1993).

The reluctance of writing and WAC scholars to embrace the tools offered through more mainstream learning analytics tools and systems, such as those included in learning management systems, may have its roots in both the metaphors on which these tools are based (the standard lecture classroom with its heavy reliance on quizzing and testing) and a long-standing awareness that the assessment of student writing performance is not well served by reductive analysis of written text. That said, the growing capabilities, speed, and accuracy of computer-based text analysis have significantly reduced the time and labor required to carry out analyses of collections of student writing—such as those produced by students in one or more classes. And writing and WAC scholars have taken notice of these tools. Examples of scholar work that employs these tools can be found in *The Journal of Writing Analytics*, established in 2016 by the editorial team of Joe Moxley, Norbert Elliot, Dave Eubanks, and Meg Vezzu and published through the Colorado State University Open Press and the WAC Clearinghouse (https://wac.colostate.edu/jwa/). The journal publishes articles that typically work with data drawn from one or more of five areas:

- corpus linguistics
- automated text analysis (often based on latent semantic analysis and natural language processing)
- content analysis
- student course behaviors
- student demographic and academic background

To date, the data analyzed in most articles published in the journal have been drawn from the first three areas. Eventually, the editors of the journal expect the data to be drawn from the other areas as well.

Several articles in the 2018 volume of *The Journal of Writing Analytics* used automated text analysis tools to explore issues of concern to writing scholars. Susan Lang (2018) studied more than 140,000 instructor comments on writing assignments completed by more than 12,000 students over a five-year period. Her findings, while restricted to a single institution, suggest the formation of a local lexicon or "canon" that shaped instructor feedback. Focusing on student writing, Thomas Peele (2018) used corpus analysis tools to explore students' use of objection, concession, and counterargument in argumentative essays. His analysis of roughly 550 source-based argumentative essays suggests that while "students introduce objections to their arguments at about the same rates as in other corpora, they are significantly less likely to concede to those objections." Moreover, he noted, "when students made counterarguments they used only a limited range of the linguistic resources available to them" (2018, p. 79). Genie Giaimo, Joseph Cheatle, Candace Hastings, and Christine Modey (2018) explored the work of tutors in writing centers, a key partner in many WAC programs, by analyzing more than 44,000 sessions notes written by writing center tutors at four institutions over a multi-year period. While their study serves primarily as a proof of concept that demonstrated the viability of a particular corpus analysis tool, it offers a promising path for subsequent analysis of tutor feedback to student writers. Similarly, Noah Arthurs' (2018) study of more than 15,000 texts created by student writers for courses across the disciplines used text analysis tools—in this case, a topic modeling algorithm—to explore how undergraduate student develop as writers over time.

The similarity of the terms *learning analytics* and *writing analytics* is intentional, according to the founders of *The Journal of Writing Analytics* (N. Elliot, personal communication, November 9, 2018). Both focus on automated analysis, both can employ statistical and text analysis methods that can be applied at scale, and both have strong application to student learning.

While many learning analytics tools focus primarily on relatively easily observed student behaviors, such as logins to a learning management system, timestamp data for completion of assignments, and scores on quizzes and exams, researchers who employ a writing analytics approach focus on the structure and/or content of student writing to explore student engagement and attitude. Liang-Chih Yu and his colleagues (2018), for example, explored the use of sentiment analysis of student writing early in the academic term to improve predictions of student success in courses. Vasileios Kagklis, Anthi Karatrantou, Maria Tantoula, Chris Panagiotakopoulos, and Vassilios Verykios (2016) studied the content of and sentiment expressed in posts to a class discussion forum to determine whether strongly negative or positive sentiments were related to success in the course. While they saw only a modest correlation between sentiment and success, their results offer a promising means of tracking student engagement and attitude as a course unfolds. Working with the much larger group of students made available through a MOOC (massive open online course), a team of Carnegie Mellon researchers (Wen et al., 2014) analyzed the sentiment expressed in discussion forum posts from more than 5,000 students who participated in three MOOCs. They found that higher sentiment rates were correlated with lower dropout rates in the course.

These studies underscore the importance of written work as an indicator of student attitudes toward the learning situation in which they find themselves. While they focus primarily on the emotional content of words and phrases, they suggest that more complex analyses might one day be used to help instructors identify students who are struggling with a course. If so, it will provide an additional rationale for using writing in courses. Work in this area has already begun, particularly in the areas of natural language processing and latent semantic analysis (Ericsson & Haswell, 2006; Perelman, 2014; Shum et al., 2016). For example, in their study of students who had completed at least one course assignment and written posts totaling at least 50 words, Scott Crossley, Luc Paquette, Mihai Dascalu, Danielle McNamara, and Ryan Baker (2016) found that combining click-stream data with natural language tools to assess student sentiment led to predictions of student course completion with 78 percent accuracy. They argue that continued work in this area is likely to lead to tools that can provide automated notifications regarding student performance in courses.

Within writing studies, the use of computer-based analytical tools is increasingly combined with more traditional learning analytics approaches, such as Moxley's (2013) analysis of correlations between course outcomes (as revealed through grades), instructor ratings of student texts, and student's rubric-based evaluations of more than 100,000 student essays. While scholars within the field of writing studies have not to date published work that has drawn on data from student information systems, click streams, and other sources of student behavioral information, we can expect that future studies will likely combine automated text analysis tools with these other sources of data. It seems likely that we will see a significant emphasis on the development of analytics tools that draw on data from student writing, their other behaviors in their courses, and their academic and demographic backgrounds.

We can also expect to see a number of tools used to support peer review, such as Eli Review, contributing data that could be used in a learning analytics dashboard. If these tools are compliant with the Learning Tools Interoperability standard (https://www.imsglobal.org/activity/learning-tools-interoperability), as Eli Review is, they could be configured to provide data to emerging data platforms, such as the Unizin Consortium's data platform (http://unizin.org). Dashboards and other analytics tools built to draw data from such platforms could then combine data from student peer review sessions with other data collected from students in a course.

For writing and WAC scholars, writing analytics in particular and learning analytics more generally have the potential to enhance our use of writing in courses across the discipline. It can help us identify students who are struggling in a writing or writing-intensive course. It can contribute to our assessments of the effectiveness of writing and writing-intensive courses. It can help us identify courses in which writing might be used to enhance student learning and success. And it can help us understand the contributions made by efforts associated with writing across the curriculum, including writing centers and writing fellows programs.

ETHICAL USES OF LEARNING ANALYTICS AND WRITING ANALYTICS DATA

Applied appropriately and ethically, learning analytics and writing analytics tools have the potential to improve learning and student success (Junco & Clem, 2015; Pilgrim et al., 2017), teaching practices (Bronnimann et al., 2018; Wise et al., 2013), and courses and learning materials (Morse, 2014; Pardo et al., 2015). However, even a casual review of the sources of data about student behaviors in a course is likely to raise concerns from thoughtful readers about how we understand and support the teaching, learning, and success of our students. By relying too heavily on predictions based on student background and academic history, for example, we can adversely shape students' trajectory through a course of study (for instance, by advising them against pursuing a particular major). By monitoring student behaviors—both in the classroom and through multimodal sources of data such as connections to wireless networks and activity on social media—we are also likely to violate student expectations of privacy. In addition, but just as important, we might monitor and assess the performance and teaching effectiveness of our faculty in ways that are both reductive and, at many institutions, would violate faculty expectations about appropriately holistic assessment of teaching practices.

We must also be aware of the increasing danger posed by the collection of data through third parties. While educational institutions are bound by Federal FERPA requirements as well as a growing number of state laws (Noonoo, 2018), both educators and vendors find themselves faced with what might charitably be called a moving target: As new capabilities emerge in tools made available through educational technology vendors and publishers, so too do the potential misuses of data captured through those tools. Consider the use of public blogs in some writing and writing-intensive courses over the past two decades. In an effort to provide students with a real external audience, some instructors asked students to publish their work in public spaces. In some cases, unfortunately, this led to the exposure of personal information and to responses from readers that were both hostile and intimidating. Now consider the kind of information that might be collected about student reading, viewing, and surfing habits as well as other information that might prove valuable in marketing and political campaigns. Consider as well the large amount of student writing that might be collected for later analysis (as has been the case with Turnitin.com's growing database of student writing). As we work with vendors and publishers who are in a position to collect both student data and student writing, we should attend not only to the capabilities provided by the software tools but also to the uses to which the data they collect might be put.

Access to information made available through learning analytics and writing analytics tools also poses ethical questions about the choice to avoid using that information. Consider, for example, the use of predictive analytics to indicate the likelihood of success in a first-year calculus course. A WAC program leader might learn that particular groups of students are more likely than not to fail to complete the course—such as those who took pre-calculus in high school rather than after enrolling in college or those who attended particular high schools. Knowing that the use of writing assignments in the course is likely to improve the learning and success of those students, the program leader would likely feel ethically obligated to reach out to the course instructor in an effort to improve the situation. What, in short, are the ethical questions that WAC program leaders face as they gain greater access to information about students' likelihood of success in a course? What are the ethical questions associated with more detailed knowledge of student performance as the course is in progress? And what are the ethical questions associated with assessment of the effectiveness of WAC courses and programs?

THREE CAVEATS ABOUT LEARNING ANALYTICS

For all the discussion above about the potential uses of learning analytics tools to enhance teaching and learning in writing and writing-intensive courses, we need to recognize that effective use of these tools will require significant efforts by instructors. Simply put, if analytics tools are to make a contribution to our courses, we need to design our courses to use them effectively. Bolting on a new technology will not transform how we teach or how our students learn. "One of our biggest challenges is that we don't design our courses so that we can collect learning analytics data," said James Folkestad, director of the Center for the Analytics of Learning and Teaching at Colorado State University (personal communication, January 17, 2019). For example, learning analytics data can provide useful information about student learning and performance in the first four weeks of a course—but only if the course is designed so that at least one assignment is collected and evaluated in that time period. Instructors in many college courses wait until later in the academic term to collect student work. Faced with a low grade on a major assignment or examination in the middle of a course, some students will drop the course or reduce their level of effort because they perceive that they won't be able to achieve their initial goals for the course.

It's equally important to recognize differences in the kinds of information provided by learning analytics tools. A number of dashboards offer "zero-day" predictions of student success. These predictions, based on student demographic information and past academic performance, typically rely heavily on algorithms that are better suited to institutional analysis of trends in courses than to accurate predictions of the success of a given student. Information about the behaviors and performance of students in a course, in contrast, offers more accurate information about the progress of that student. When combined with demographic and academic information, it can be highly predictive. But it's important to recognize that many students either fail to live up to those predictions or significantly overperform the predictions. What students do in a course, in short, is far more important than the destiny painted by their demographic backgrounds.

Finally, it's important to recognize that learning analytics tools are only as useful as the information on which they are based. A tool that relies on the use of a particular learning management system's eReader for data about which students are reading an assignment and how much of the reading they've completed will not tell you anything of value about students who downloaded the reading to their phone or laptop. You would no doubt be warned that these students are not completing the reading assignment. That information would be inaccurate. Similarly, a student might log in to a learning management system and then leave to get lunch. The login data might indicate the length of time that the student was signed into the system—hours, in this case—and inaccurately indicate that the student was highly engaged in the course.

Writing and WAC scholars who might find it attractive to use the predictions available through learning analytics tools would be wise to keep these limitations in mind. To the extent that these tools allow us to see things we might otherwise miss, they can be useful. But even in those cases, we should interpret what these tools tell us through the lens of our experiences working with students in our classrooms.

CONCLUSIONS

Within the field of writing studies, journals are publishing work that draws fully or in part on learning analytics data and tools. *The Journal of Writing Analytics* published its second volume in December 2018 and a companion conference has been held since 2012. While learning analytics is still an emerging scholarly field (e.g., Siemens, 2013), it has important implications for the study of writing—not least of which is its characteristic use of multidisciplinary teams to carry out its work, a practice similar to the multidisciplinary approach often employed in WAC.

That said, there are certainly drawbacks associated with using tools and analytical techniques that are still in their infancy. As we explore the use of learning analytics and writing analytics, we should consider carefully the potential drawbacks—and even dangers—associated with current and potential tools and practices. We must understand thoroughly how they might be used in ways that can harm students and faculty, particularly in the areas of student and faculty privacy, commercialization of data, the use of predictive algorithms that might discourage students from pursuing their desired courses of study, and the use of data to inform (or, worse, constitute the bulk of evidence for) faculty evaluations. This latter concern is particularly important in a field in which a large percentage of faculty are employed in contingent positions.

For writing studies more generally—and within WAC more specifically—the use of learning analytics data holds a number of important implications for curriculum and program design and, most important, for the success of our students. We would be wise to attend to the kind of learning analytics data that might be drawn from courses that assign writing, to ethical issues associated with the use of this data, to issues related to privacy and surveillance, and to concerns about commercialization of data drawn from and about students. Exploring these issues will help us better understand and foster the conditions under which learning analytics tools—and, more specifically, writing analytics tools—might be used effectively and appropriately to enhance the learning and success of our students.

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