Invited Article

Directions in Writing Analytics: Some Suggestions

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Over the past decade, we've seen significant growth in the use of learning analytics in higher education. Early work in the area tended to focus on making arguments about how "big data" could inform efforts to improve teaching and learning in disciplines across the university and to lay out a framework for understanding both benefits and potential harms associated with the use of learning analytics data (Daniel, 2015; Fournier, Kop, & Sitlia, 2011; Retalis et al., 2006; Siemens & Long, 2011; Viberga et al., 2018). More recent work has taken up additional areas of inquiry, including ethics and privacy (Cormack, 2016; Gursoy et al., 2017; Pardo & Siemens, 2014), interventions intended to enhance student learning and success (Drachsler & Greller, 2016; Macfadyen et al., 2014), and the potential use of "nudges" and other automated communications to support self-regulated learning (Howell, Roberts, & Mancini, 2018; Pilgrim, Folkestad, & Sencindiver, 2017).

Writing analytics, in contrast, is a more recent program of research (Moxley, 2013; Moxley & Walkup, 2016; Moxley et al., 2017; Shum et al., 2016), although the analysis of quantitative data to support curriculum design in writing courses extends into the early part of the twentieth century, and the use of text analysis builds on a long tradition of linguistic analysis. In an odd twist, while the name itself was coined by a pioneer in learning analytics, a disconnect exists between much of the work in writing analytics and the emerging field of learning analytics. This disconnect extends to both the goals pursued by writing analytics researchers within writing studies and those who are aligned with learning analytics and to the methods used by these two groups of researchers.

Below, I explore the emergence of the term writing analytics, its connections to learning analytics, and potential directions for an expanded understanding of writing analytics. I also consider how work in these two areas of analytics research might productively inform each other.

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The Larger Context: Learning Analytics

Learning analytics is a capacious term that covers activities involving the use of data about and/or generated by students to assess and predict their success as learners. Learning analytics activities are used for three primary purposes: (1) to estimate the probability of student success in a course prior to and during the offering of a course; (2) to identify points at which instructional interventions might increase the likelihood of student success in a course; and (3) to support retrospective analysis of instructional materials, instructional interventions, and instructor teaching effectiveness. The latter purposes are often pursued as part of course redesign efforts and can be used as well to inform the development of new courses.

Instructors, academic advisors, and students typically gain access to reports and analyses (often presented as charts or tables) of learning behaviors through four sets of tools. Commercial learning analytics products are available through companies such as Acrobatiq, Barnes and Noble Education, and Civitas. Educational organizations such as Unizin (unizin.org), a consortium of large higher-educational institutions, are developing tools that can be used by their members. Some of the larger publishers, in particular McGraw-Hill and Macmillan, have made substantial investments in learning analytics reporting for their learning management systems (LMS) and adaptive assessment tools. And several LMS providers, including Canvas and Blackboard, offer dashboards that help instructors view student activities within the LMS.

Data and information used in learning analytics tools include:

- Information about student activities within learning management systems (LMS), such as Canvas and Blackboard (Daniel, 2015; Zhang et al., 2018). Typically, this data focuses on student logins, visits to pages and other resources within the LMS, posts to discussion forums, performance on quizzes and examinations, completion of assignments, and so on. Canvas offers a built-in dashboard that allows instructors to view student use of the system. Over time, it is likely that the capabilities of these dashboards will grow to include fine-grained analysis of student behaviors and, potentially, predictions of student success in the course.
- Data produced by adaptive assessment tools, such as those offered by McGraw-Hill and other publishers (Lewkow et al., 2015). Largely because of the extensive and fine-grained nature of the data collected by these systems, they are typically analyzed within tools provided by the publisher.
- Data produced through interactions with eReaders and media viewers, such as the Unizin consortium's Engage eReader (Junco & Clem, 2015; Shoufan, 2018). These tools typically provide data that can be viewed by instructors within the eReader or media viewer platform. In some cases, including Engage, it can also be ingested by learning analytics platforms such as Barnes and Noble Education's LoudSight.

- Information drawn from communication tools, such as discussion forums (including those within an LMS) and email systems. This kind of information is frequently used in sentiment analysis (Kagklis et al., 2015; Wen, Yang, & Rosé, 2014; Yu et al., 2018;). Some of these systems can provide data that can be analyzed within a learning analytics tool.
- Information drawn from instructional software programs. This might include peer review tools such as Eli Review (elireview.com) and My Reviewers (myreviewers.org). In some cases, data from these kinds of tools can be ingested by other learning analytics systems and analyzed in conjunction with other information, such as student demographic data and academic history.
- Data drawn from student information systems, including demographic information and records of past academic performance (Wong, Li, & Choi, 2018). This data is frequently ingested by learning analytics platforms such as Barnes and Noble Education's LoudSight and EAB Navigate and used in the algorithms they use to predict student success.
- "Multimodal" data drawn from activities that are not directly connected with a class, such as attendance at tutoring sessions, connections to campus Wi-Fi routers, and posts to social media (Di Mitriet al., 2018). In addition, a number of scholars (SoLAR, 2016) have explored capturing audio, video, and other information as students learn (in both laboratory and non-laboratory settings).

Learning analytics platforms and tools provide a range of reports. These are often presented via interactive dashboards that allow users to customize the output to respond to specific questions. For example, a dashboard might allow filters or limits to be applied, allowing the user to view results for a specific group of students or students whose entering GPA is at or below a particular level. The primary functions provided by learning analytics tools are descriptions of student behaviors, predictions about student success in a course, and messaging. Descriptive reports might focus on the number of students who have completed an assignment or logged in to an LMS during a particular period of time, or they might focus on scores on a quiz or exam. They might also provide information about the number of students who read an assignment and how many pages were read. Predictions of students' likelihood of success in a course are sometimes referred to as "risk scores" or "success scores." Messaging can include "nudges" and "alerts." Nudges are sent to students to inform them about upcoming or missed deadlines. They can also be sent to encourage students to engage in behaviors that are likely to lead to increased success in a course. Alerts are sent to instructors or academic advisors to inform them of students who might benefit from interventions. For example, an advisor might receive an alert that a student is in danger of failing a course, while an instructor might be informed that a student missed an assignment deadline for the second or third time or has not logged in to the LMS for more than two weeks.

In general, while use of learning analytics tools is becoming more common in higher education, they are viewed with skepticism by many scholars—as is appropriate, since these tools are still in an early stage of development (I discuss this in greater detail in a chapter in the forthcoming proceedings of the 2018 International Writing Across the Curriculum conference; see Palmquist [2019]). Moreover, skepticism is warranted because learning analytics tools have the potential to shape the academic paths taken by a large number of students. Used without an awareness of their limitations, the predictions they provide might prevent students from defining and reaching career and life goals that they might, without intervention, achieve. Used with an appropriate level of skepticism and with an overriding concern for the best interests of our students, however, learning analytics tools have the potential to help students learn and succeed at levels they might not otherwise achieve. As writing specialists, we can view the new tools emerging from work in learning analytics as potential aids in our efforts to help our students improve as writers and thinkers.

Focusing on Writing: Writing Analytics

Writing analytics refers to the use of quantitative data (including quantitative data derived from qualitative analysis of written text) to assess the quality and characteristics of student writing and activities associated with writing instruction. While work in this area has a long history in writing studies, and while key scholars in writing studies have been engaged in using big data to explore student writing for a number of years (see, for example, Moxley, 2013, and Moxley & Walkup, 2016), the term itself can be traced to Simon Shum (2015), an educational researcher with an interest in using learning analytics to explore writing. In 2016, Shum 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)

While this definition is promising, the "measurement and analysis" of writing that Shum and his colleagues have employed have to date focused largely on automated tools that have emerged from latent semantic analysis, natural language processing, corpus linguistics, and style and grammar checking routines. The goal of this work, Shum has noted, is "to understand the potential of the (sometimes controversial) topic of providing students with automated feedback on their writing" (2017). While Shum's work shows promise, it is largely uninformed by scholarship in the field of writing studies. As a result, it seems to have focused primarily on surface-level characteristics of writing and has not taken advantage of opportunities to go beyond them.

Other scholars have embraced the term "writing analytics," often without an awareness of the origin of the term or its connection to efforts in learning analytics. Drawing on techniques associated with corpus linguistics, data analytics, and content analysis, among others, they have begun exploring topics such as the formation of instructional lexicons among communities of writing instructors (Lang, 2018), the structure of arguments in student essays (Peele, 2018), the development of student writers over time (Arthurs, 2018), differences in the text produced by student writers in various disciplines (Crossley et al., 2017), and the work of tutors in writing centers (Giaimo et al., 2018). These studies, all published in *The Journal of Writing Analytics*, point to an expanded set of purposes to which automated methods might be put in our field. Those purposes include, potentially, exploration of student writing and reading processes, the feedback provided by instructors and writing center tutors, the impact of conventions shaped by genre and discipline, and understanding how students develop awareness of writing strategies associated with argumentation, reflection, and analysis.

While scholars outside the field of writing studies and linguistics, such as Shum, have focused largely on the use of automated tools to explore writing-related learning outcomes, scholars within the two fields have embraced a more robust set of tools and analytical methods. Commenting on this difference, Norbert Elliot (personal communication) argued that the key difference is that writing analytics is construct-based, while learning analytics is not:

> Learning analytics is not construct-based. Writing analytics is. Indeed, those who have published in the *Journal of Writing Analytics* seem, on the whole, to be leaning toward a language arts model of writing (writing as understood in a network of reading, speaking, and listening) as understood within four domains: cognitive, intrapersonal, interpersonal, and neurological. This kind of fine-grained construct articulation allows an actionable framework for our research.

The efforts that have emerged from our field's emerging focus on writing analytics are promising, and we can expect future work to not only build on them but also to employ both a larger set of methodological tools and a more robust set of research goals. Foundational work in this area is already being carried out, as evidenced by the functional taxonomy of writing analytics developed by Susan Lang, Laura Aull, and William Marcellino (this issue). Their goal, to create "a purposeful mapping that identifies both established and nascent research questions," is ambitious and highly generative, pointing both to the directions in which the field of writing analytics is likely to move in coming years and offering insights into how we might begin to address fundamental questions that are well suited to exploration through a writing analytics approach.

Expanding the Reach of Writing Analytics: Drawing on Learning Analytics Data and Tools

Beyond our growing use of tools associated with corpus linguistics, data analytics, and content analysis, we can turn to a larger set of analytic tools to understand the learning processes of student writers. While controversial (see, for example, Nicky Hockly's [2019] recent review of automated writing evaluation), tools associated with natural language processing and latent semantic analysis can offer insights into our analysis of student texts. Writing scholars are wise, however, to avoid over-reliance on these tools. They are at best reductive and, as scholars such as Anne Herrington and Charles Moran (2006), Les Perelman (2012, 2014a, 2014b), and Peter Greene (2018) have argued, they are often inaccurate. Yet, used with appropriate caution (and, as I've mentioned above about learning analytics tools in general, skepticism), they have the potential to help us gain insights into aspects of student writing performance and into teaching and learning practices that might lead to improved learning outcomes.

More importantly, perhaps, we can turn to the larger set of tools used in learning analytics to understand how our students learn to write, the points in a course at which they encounter difficulties, and instructional strategies we might employ to improve their learning and success. That is, we can use learning analytics data and tools to investigate the writing classroom in much the same way that we are looking at teaching and learning processes and outcomes in mathematics, sociology, and chemistry. This includes exploring patterns revealed through exploration of the connections between teaching and learning behaviors (such as use of the LMS and adaptive learning tools, reading and viewing behaviors, and visits to writing and tutoring centers, among others) and information about our students (such as their academic history and demographic background). If we see patterns, for example, that suggest that first-generation college students benefit from particular teaching practices more than students who come from different backgrounds, then we can follow up with additional studies and, in the long run, we might be able to develop more effective teaching practices for that group of students. Similarly, if we see patterns that suggest a decrease in student learning performance when particular practices are used, we might begin to explore the underlying causes of that decrease.

The point: Scholars with an interest in writing analytics can turn to a much larger set of tools than we have used so far. We need not turn away from tools that have proven useful—particularly those drawn from corpus linguistics, data analytics, and content analysis. Instead, we can combine our use of those tools with strategies and methodologies used in learning analytics. Doing so will expand our reach and allow us to see patterns that, perhaps, would not otherwise be easy to observe.

Agenda Items for Writing Analytics Research

As writing scholars, we should be wary of allowing those outside our field to define "writing analytics"—especially when some of those who have embraced the goal of improving student writing seem to lack an awareness of the scholarship in our field. We should instead lay out an agenda that reflects the values and goals that have long characterized the field of writing studies.

Enhancing Teaching Effectiveness. We have long focused on course design and redesign. We should consider how writing analytics research might aid us in these efforts. We can use insights from writing analytics research to inform assignment design and sequence, to explore activities and assignments that lead to increased interaction between students and among students and instructors, and to gain a better understanding of the relationships among feedback (types, amounts, frequency) and markers of success (increased time spent writing and researching, increased revision, increased writing quality, and increased success in subsequent courses).

Improving Student Learning and Success. It seems likely that studying how writing students interact with instructional technology might help us gain insights into activities and assignments that lead to increased learning, performance, and success. We might work to identify key student behaviors (in the LMS and in the larger learning environment) that are associated with improved learning outcomes. We might explore whether messages (nudges) sent by a learning analytics system might lead to improved student learning (and whether they do not). We might focus on what student writing, email messages, and posts to class discussion forums can tell us about our students' learning processes, motivations, and attitudes toward work in the course. And we might consider whether writing analytics data can help us identify students who are struggling academically and emotionally (before we might otherwise have observed it).

Improving Feedback on Writing. We can, as scholars such as Susan Lang (2018) and Chris Anson (Anson & Anson, 2017), among others, have already begun to do, explore the development of shared lexicons in classrooms and writing programs. And we might use data revealed through writing analytics research to help us improve our understanding of productive feedback practices.

Identifying Courses that Would Benefit from the Use of Writing. Writing across the curriculum specialists might find that data from learning analytics tools can help identify courses in which writing-to-learn and writing-to-engage activities might enhance student learning and success. WAC specialists might also use writing analytics data and tools to assess the impact of WAC efforts, including success in subsequent courses, and explore strategies for improving learning outcomes in those courses.

Improving Writing Center Outcomes. Similarly, writing analytics data and tools can be used to explore practices within a writing center, both to improve outcomes within a particular center and to contribute to our growing understanding of effective practices, including those related to social justice.

Developing a Deeper Understanding of Intersections Among Genres, Contexts, and Purposes. Writing analytics, with its strong connections to corpus analysis, is well suited to providing insights into how genres function in varied social, instructional, and civic contexts. This work can expand the growing understanding of genre within the field of writing studies, certainly. It can also offer, through its fine-grained analysis, insights into how genres function differently in varying instructional settings.

This agenda focuses largely on the teaching and learning of writing. For example, writing analytics research has the potential to improve learning not only in particular types of courses, but also in subsequent courses. By exploring patterns within courses (associations among writing quality, grades, student and instructor behaviors, interactions, and engagement in particular activities), as well as in courses student take in subsequent academic terms, we can gain insights into practices that affect learning not only in a particular course, but also throughout an academic career. But our agenda need not—and I would argue should not—focus solely on writing in instructional settings. We have the opportunity to use writing analytics to explore the use of writing in social and civic settings. Certainly, writing analytics has great potential for studying genre in such settings. This is only a starting point. We should consider how it might be used to explore the impact of rhetorical action in the wide range of settings in which writing is produced and used.

Recommendations

Currently, the overlap between writing analytics and learning analytics seems smaller than it should be. As a field, we seem to be focusing primarily on what might be termed traditional methods, particularly those drawn from corpus linguistics. We should consider using a larger set of tools and methods, including those used successfully in learning analytics research in other fields. We should not do so without skepticism, but we should consider how tools and methods used elsewhere might inform our research and allow us to gain insights not afforded by our current toolset.

This will, without doubt, require significant effort and discretion on the part of researchers. Using new tools and methods requires an effort to understand the assumptions that underly them – assumptions that are often at odds with our ethical stances as teachers. For example, the risk scores that some learning analytics platforms provide before a course begins are based solely on past performance and demographic information. Using these scores—if we choose to use them at all—carries significant risk of biasing our understanding of individual students and groups of students. Effective use of these tools will require significant efforts by faculty. It is possible that wide use of these kinds of predictive analytics might have benefits, but that is likely to be the case only when instructors have a clear understanding of the limitations and built-in biases of the tools.

Perhaps most important, work in writing analytics can provide a framework for scholars outside of writing studies who seek to study writing as part of larger learning analytics efforts. Currently, for example, a great deal of effort is being put into sentiment analysis (Kagklis et al., 2015; Wen, Yang, & Rosé, 2014; Yu et al., 2018;). Yet my colleagues in linguistics tell me that sentiment is only one of many aspects of language than can be assessed productively. We might also look, for example, at interaction patterns and cooperation to gain insights into student learning and social action. Similarly, the comparatively uncritical use of programs that assess student writing is an area worthy of our attention. Publishing research that explores the limitations of these tools would be a service not only to other researchers but also to students and instructors.

As a field, we have an opportunity to take a significant leadership role in writing analytics—and, perhaps, writing studies more generally. Doing so will help us inform the efforts of learning analytics researchers outside the field of writing studies, offering both a corrective to current practices and a set of tools and methods that can allow learning analytics researchers to gain a deeper and more accurate understanding of student learning and success. In addition, by expanding our efforts in writing analytics research, we have the opportunity to improve our understanding of writing pedagogy, composing processes, genre, and the impact of writing in social and civic settings, to name only a few important areas within writing studies.

Note

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