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The racializing forces of/in AI educational technologies*

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ABSTRACT
In this article, we examine the sociopolitical implications of AI technologies as they are integrated into writing instruction and assessment. Drawing from new materialist and Black feminist thought, we consider how learning analytics platforms for writing are animated by and through entanglements of algorithmic reasoning, state standards and assessments, embodied literacy practices, and sociopolitical relations. We do a close reading of research and development documents associated with *Essay Helper*, a machine learning platform that provides formative feedback on student writing based on standards-aligned rubrics and training data. In particular, we consider the performative acts of the algorithm in the *Essay Helper* platform – both in the ways that reconstitutes material-discursive relations of difference, and its implications for transactions of teaching and learning. We argue that, through these processes, the algorithms function as racializing assemblages, and conclude by suggesting pathways toward alternative futures that reconfigure the sociopolitical relations the platform inherits.

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Artificial Intelligence (AI) and big data analytics have recently found uptake in education research, policy, and practice. One such area under rapid scholarly and corporate development is in learning analytics – a machine learning technology that extracts patterns from data-flows to inform and augment the transactions of teaching and learning (Siemens and Baker 2013).[1] Using AI technology, learning analytics are purported to optimize the efficiency of and responsiveness to student learning experiences and, in doing so, to address inequities in formal and informal education.

While the promise of learning analytics aligns with policy and pedagogical priorities for addressing educational inequity, we know little about its wider sociopolitical implications. How might algorithmic biases and political relations inhere in the sociotechnical assemblage of learning analytics? How might AI technologies reconfigure formations of difference in curriculum, instruction, and learning? Advances in AI technologies and their integration into learning environments need to be understood in relation to such sociopolitical implications (Dixon-Román 2017). Thus, focused inquiry on AI technologies and learning analytics are needed to better understand the work of such platforms, and the associated mechanisms and practices that might further the aims of educational equity.

BeowulfEd's Essay Helper[2] is one such example of a learning analytics platform. *Essay Helper* uses supervised machine learning to provide formative feedback on secondary student writing. Aligned with state policy standards in the United States, *Essay Helper* promises to significantly improve schools' on-average test scores. In this manuscript, we examine how the data and algorithms of

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learning analytics like *BeowulfEd's Essay Helper* may inherit sociopolitical relations. How might bodies and classroom practices be shaped by the performative acts of the platform? How might material-discursive relations of difference be reconstituted through its cloak of algorithmic objectivity? We employ a new materialist theory of how the performative acts of the algorithm's 'soft(ware) thinking' (Parisi 2013) function and become racializing assemblages (Dixon-Román 2016). By closely reading research and development texts from *BeowulfEd's Essay Helper*, we examine how this platform may, too, be entangled in such racializing processes. This is not a focus on politics of identity or representation, as is the case with other studies on algorithmic bias (Eubanks 2017; Noble 2018), but rather an examination of how sociotechnical systems become sociopolitical forces shaping the potential transactions of teaching and learning. Finally, we consider the ethical and policy implications and discuss alternative futures that center the racializing assemblages of algorithms.

Literature review of learning analytics

Learning analytics refers to the field of research and development that extends the data science methods of AI to educational processes. Where traditional data science uses algorithms, storage systems, and machine learning protocols to organize and extract patterns in datasets and to apply the resulting associations in public policy, disciplinary problem-solving, and industrial practice (Kitchin 2014), learning analytics orients such procedures toward pedagogical encounters. Building on earlier work in educational data mining – the process of amassing keystroke, clickstream, and natural language data from online learning contexts (Siemens and Baker 2013) – learning analytics arranges such flows into 'structured data' (Cope and Kalantzis 2016) that can visualize and track student performance or aid in instructional decision-making (Knight, Shum, and Littleton 2014). In their foundational article on the topic, Long and Siemens (2011) delineate a taxonomy of learning analytics, arguing that combinations of data mining, predictive modeling, and intelligent platforms hold transformational potential for education. Such procedures, they suggest, can 'penetrate the fog of uncertainty around how to allocate resources, develop competitive advantages, and most important, improve the quality and value of the learning experience' (p. 40). In years since, as learning analytics associations, conferences, and journals have emerged, enthusiasm for this potential has continued to grow. A report from the Learning Analytics Workgroup states the ambitious 'endgame' for learning analytics as, 'personalized cyberlearning at scale for everyone on the planet for any knowledge domain' (Pea and Jacks 2014, 17).

Such visions of data-driven learning are not new, but emerge from a long lineage of techniques for making education personalized and adaptive – from automated learning and programed instruction to Skinnerian 'teaching machines' (Glaser 1965; Skinner 1968). However, where these mechanisms used data to pair students with developmentally appropriate curricula or guide teachers in making interventions, learning analytics uses AI technologies to process stores of information and optimize and reconfigure educational environments themselves. Early iterations in literacy education included computer-adaptive assessments which analyzed students' comprehension of texts; but over time, more sophisticated metrics have allowed computers to undertake the complex task of parsing students' *production* of texts – namely, short- and long-form writing (Cope et al. 2011). With machine learning algorithms, developers use human-graded essays to train computers to parse natural language features like textual cohesion and word frequency (McNamara et al. 2014). This process renders immediate evaluative feedback on student compositions with striking precision – through multiple tests, machines have been shown to grade writing with reliable equivalence to humans (Warschauer and Grimes 2008). Importantly, such tests have relied on learning analytics as a summative measurement – that is, an assessment of writing in a completed state, not offering formative suggestions while it is in-process. With the increased emphasis on developmental writing in college- and career-readiness standards under the *Every Student Succeeds Act* (2015) and the growing research base stressing formative assessment in writing instruction (Shute 2008), developers have continued to search for more precise means to automate and systematize formative feedback through expanded uses of AI and learning analytics (Woods et al. 2017).

Of course, the use of such methods are not neutral: developments in AI-mediated instruction carry with them a range of ethical questions related to power and privacy. Scholars have argued, for example, that the consolidation of data in the hands of commercial platforms not only alters the location from which we theorize educational practice – from the lived dynamics of classrooms to the abstract datasets of proprietary systems – but also opens students to invasive new modes of surveillance (Williamson 2017). Given the racialized histories of surveillance (Browne 2015), these mechanisms may contribute to, rather than ameliorate, the reproduction of educational inequity. Crucially, such ethical concerns extend further – to the embodied act of learning itself. Recently, scholars have theorized learning analytics and algorithmic processes as socio-material assemblages that form and shape students in particular ways (Dixon-Román 2016; Scott and Nichols 2017; Perrotta and Williamson 2016). Where Pea and Jacks (2014) define learning analytics as the 'creation of a model of the learner,' these socio-material perspectives recognize how such protocols also create learners of a certain model – which raises questions about what subjects these analytical procedures produce (Slade and Prinsloo 2013). AI and learning analytics, then, serve a biopolitical function, disciplining minds and bodies through contact with algorithms, protocols, and computational logics – this is especially so as these datafied infrastructures are brought to bear on forms of teaching and learning long identified as embodied practices, such as writing.

Writing as embodiment & sociotechnical practice

In *Of Grammatology*, Derrida (1974) deconstructs the long-held privileging of speech over writing. Although both were understood to be signs that mediated the expression of the linguistic referent, speech was privileged because of an assumed presence that writing did not possess. Writing was understood as a signifier of a symbol of speech, to which speech was a symbol of the linguistic referent. Derrida not only questioned the assumed metaphysics of presence in speech but ultimately argued that they are both derivative of thought and mutually constitutive. This deconstructive operation has several implications, one of which is a reconceiving of writing as a form of speech act, an embodied act.

The body of speech acts have been theorized in numerous ways however recent work in new materialisms has reconceived of the ontology of matter, the body, and the discursive. Drawing from quantum physics, Barad (2007) develops her 'agential realism' by rethinking the discursive as a process of *material* reconfigurings of the world via a process of iterative intra-actions. Intra-action (rather than interaction) is a performative process of mutual constitutions between objects or agencies within phenomena. As relational actions, intra-actions are a performative process not just of humans but matter too, where agency does not exist in any one entity but is an achievement of multiple intra-acting phenomena. For Barad, matter '… *is substance in its intra-active becoming—not a thing but a doing, a congealing of agency. Matter is a stabilizing and destabilizing process of iterative intra-activity*.' (Barad 2007, 151). All bodies come to *matter*, not just human bodies but the atomistic ontologies that make up the composite materialization of bodies. As an entangled expression of the world, the material conditions of the body matter 'because *matter comes to matter* through the iterative intra-activity of the world in its becoming' (Barad 2007, 152; italics in the original). This reconceiving of the ontology of the matter of the body has profound implications for the bodies of education, including writing.

Writing has always been a material act (Haas 1995). Leander and Boldt (2013) draw on Deleuze and Guattari (1987) and to frame literacy practices as embodied and emergent. Literacy is not just individuals decoding (or encoding) words on a page, but a contingent unfolding where the text is understood as an artifact in relation with the body of the reader. The body of the reader is also an assemblage of affective intensities that is in contingent relation to its environment, including the text. Leander and Boldt describe a case of a teen reading manga and suggest a shift in analytical focus from the practices of literacy to the movement, process, and intensities of the body. They demonstrate how the student's reading of manga enters into the other flows of the environment, including the bodily movement and intensities of the subject, what they characterize as the child 'becoming-manga.' This rhizomatic analysis of 'becoming-X' is especially relevant for AI learning analytics platforms that are trained on a set of data and designed using a set of structures that constitute 'proper' versus 'improper' forms of writing in their unseen protocols. The becoming-X in this rhizomatic process may be circumscribed based on the forces (e.g., training data, values, curriculum, policy) that have been normalized into the sociotechnical system of the platform.

Accordingly, the learning analytics platform is not a passive prosthetic to human understanding, but is actively reading/scaling the student while the student is simultaneously reading and acting on/with/in it (Dixon-Román 2016). This moves us beyond traditional conceptions of writing skills being a cognitive or sociocultural process toward an embodied process of relational ontologies; one that does not assume the body to be fixed, passive, and determinate, but constantly mattering as it intra-actively reconfigures indeterminate, porous boundaries of the body. For Barad (2007), this comprises the learning analytics platform and it is through the iterative intra-acting practices of the sociotechnical system that produces determinate boundaries of what's possible and impossible of the embodied process of writing. Thus, the material act of writing in learning analytics may not be an open-ended becoming, but is likely circumscribed based on sociocultural, political, and material forces. It is for these reasons that writing analytics platforms must be studied as sociomaterial and sociotechnical processes.

As an embodied act, writing is also raced, classed, and gendered. For instance, research has found that Black girls' literacies are often unacknowledged in classroom spaces (Muhammad and Haddix 2016). As a material and discursive practice, literacies are formed and shaped by norms of cultural communities and, as such, may be valued, overlooked, or misrecognized in different contexts (Freedle 2003; Lee 2001). Thus, certain literary acts may be recognized by some and misrecognized by others. Scholars have shown, for example, how immigrant students' identities and literacy practices may position them at a 'deficit' by school systems (Campano 2009). These material and discursive forces elucidate how the embodied act of writing is shaped by racialized, classed, and gendered formations of difference. These same formations have also been examined and found in sociotechnical practices of algorithms too (Dixon-Román et al, In Press; Eubanks 2017; Noble 2018).

AI & algorithmic reasoning as racializing assemblages

Although AI is assumed to be an objective practice of instrumental reason, we are increasingly seeing how algorithms may become part of a larger sociotechnical apparatus of sociopolitical relations. To examine this in the context of learning analytics, we use the concept of algo-ritmo (Dixon-Román 2016) to analyze learning analytics as a sociotechnical assemblage. Algo-ritmo seeks to account for both the immanent agencies of algorithmic acts and the ways those acts become racializing assemblages.

In theorizing how algorithms become racializing assemblages, the first author (2016) has argued that algorithms inherit sociopolitical relations of society through data. Data are not pure, objective extractions of the world but are assemblages that are materially and discursively produced from forces of human and more-than-human ontologies, including sociopolitical relations (Dixon-Román 2017).

For algo-ritmo, algorithmic reasoning is not understood to be mechanical operations that are contingent on human intervention or design. In accordance with Parisi (2013), algorithms are actual entities that consist of finite operations of calculation as well as incomputable data sequences. As actual entities, they are sociotechnical ontologies that are always in process of becoming in relation with sociopolitical systems, legal practices, (re)programed inputs, and data assemblages. These are not simply humanly designed technologies; rather, as algorithms process and are trained on data assemblages they become more-than-human ontologies. As Parisi argues, operating between the space of finite algorithmic operations and the incomputability of the world's infinite complexity (i.e., information) are forms of speculative reason that are immanent to computation.

As agencies that inherit sociopolitical relations via data assemblages, the immanent forms of reasoning and more-than-human performative acts of algorithms become racializing assemblages. Weheliye's theory of racializing assemblages seeks to more adequately account for the processes of power and racializations of the body/flesh. As argued by Weheliye (2014), racialization is not to be reduced to race or racism but is the *process* of differentiation and hierarchization that produces the assemblages of race, gender, class, sexuality, and dis/ability among other structural relations of 'difference'. The sociopolitical process of racialization are perpetuated via technologies and sciences (among other things) and require 'the barring of nonwhite subjects from the category of the human'. Thus, the data and code of algorithms inherit sociopolitical relations becoming a performative force of racializing assemblages.

In what follows, we examine the ways in which the algorithmic reasoning of AI, as materialized in a learning analytic platform on writing, becomes racializing assemblages. As will be discussed below, sociopolitical relations of racializations become part of the architecture of the AI learning analytic platform in at least two ways. First is by way of the rationalities behind the design of the platform and the operationalized rubric of state standards. The second is more posthumanist via the algorithmic intra-action with data assemblages and through this process (re)configuring the architecture of the algorithm to becoming a racializing assemblage. By putting the concept algo-ritmo to work in a close reading of the existing technical and research reports that undergird the development of a learning analytic platform, we illuminate the process of the AI algorithms 'becoming-sociopolitical'.

Case study of BeowulfEd's Essay Helper

Discussion of case study method & analysis

In what follows, we examine how the datafication of education, as materialized in learning analytics, becomes racializing assemblages. To do so, we present a case study of one application of learning analytics: the use of a supervised machine learning algorithm that provides automated, formative feedback on student writing. For data, we draw on a close reading of fourteen key texts provided to us by the case study institution, *BeowulfEd* (Table 1). Our close reading is a deconstructive reading of these key text with a focus on processes of racializing assemblages. This approach is a speculative inquiry that is much more culturally embedded and gets at the sociopolitical nuances of in and between the texts. The texts include three grant proposals; three conference proceeding articles; a press release; three technical reports; and four whitepapers. Collectively, these texts document both the long-term project of developing a learning analytics tool and the efficacy of such educational

Table 1. Document codes of the key texts for this case study.

Code	Description
DOC1	Website about page for *Essay Helper*
DOC2	2013 press release announcing the launch of Essay Help
DOC3	2013 funded grant proposal, Bill and Melinda Gates Foundation
DOC4	2013 confidential internal report on market drivers and development challenges
DOC5	2014 pilot program administrator handbook
DOC6	2014 Smarter Balanced technical report
DOC7	2014 grant proposal, Department of Education
DOC8	2014 funded round-two grant proposal, Bill and Melinda Gates Foundation
DOC9	2015 White paper describing what *Essay Helper* is and how it works.
DOC10	2017 Conference paper on *Essay Helper* for Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining
DOC11	2018 Position paper on implementing algorithms in education
DOC12	2018 conference paper on automated essay scoring without construct validity
DOC13	2018 conference paper on district implementation of automated writing feedback
DOC14	2018 Conference paper on *Essay Helper* for Proceedings of the ACM Conference on Learning Analytics and Knowledge

interventions. In reading these texts, we highlight two ways the algorithms that power learning analytics platforms form and shape students and educational practices. This will help to illuminate how algorithms inherit and produce relations of difference and generate gendered and racialized predictions.

Description of BeowulfEd's Essay Helper

Essay Helper is a platform that provides immediate formative feedback on students' in-process writing. Participating schools and classrooms are given a bank of writing prompts, which are then assigned to students, who use them compose short- and long-form essays through the *Essay Helper* interface (Figure 1). As an draft is being created, *Essay Helper* tracks students' progress toward a target word-range through an interactive word-count. Upon completion, the platform generates feedback on the composition using a machine learning algorithm trained with student-written and human-graded essays. The algorithm parses the text and provides line-item commentary, prompting students to address matters of cohesion and text variety. The essay is also scored against a rubric, allowing students to see how changes in individual sentences might alter their work's progress toward effective organization, clarity and focus, use of evidence, and language and genre awareness. Teachers, then, use this data to provide additional formative instruction, or to make subsequent assignments in *Essay Helper's* database.

Importantly, this snapshot of *Essay Helper*'s current configuration elides a longer history of its development. While platforms may appear ready-made, they are actually a precarious, collective achievement: an assemblage of socio-technical and socio-economic interests, layered together and pulling the constellation in competing directions as it takes shape over time (Nichols and Stornaiuolo 2019; van Dijck 2013). In other words, the version of *Essay Helper* implemented today is not an inevitable outgrowth of research and development; its unfolding has, from the beginning, been shot through with contingencies. For example, in spring 2013, the platform – then called *WriteGuide* – was the brainchild of a few computational linguists interested in applying machine learning to secondary writing instruction. In a proposal for Gates Foundation funding, the developers explain they envision the project as a free, open-source program. At the time, it was imagined as a resource for teachers who, due to energy and time constraints, often had to 'forego time-intensive assessments that capture deep learning, such as peer-discussions, extended essays, or revision opportunities'

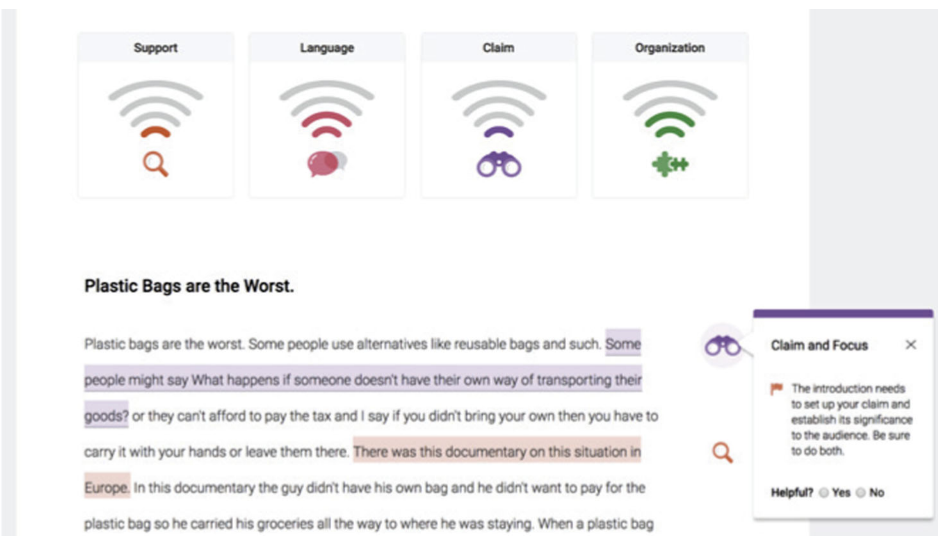

Figure 1. Example of *Essay Helper* User Interface with rubric scores and essay feedback.

(DOC3). The platform was meant to facilitate such interactions, providing a medium for classroom-level peer-response and a standards-aligned assessment tool that would free teachers to focus less on grading and more on 'deep learning.' However, by summer 2013, the platform's socio-economic dimensions shifted: with funding from the Gates Foundation, and new partnerships with high-stakes testing companies, *WriteGuide* opted to reorient its technical design, dropping its interest in peer-collaboration to focus exclusively on automated assessment.

This shift has, since then, manifested in two different strands of partnerships shaping the platform's development: schools and testing companies. On one hand, *WriteGuide* retained its interest in classroom practice, and in early 2014, deployed pilot programs in high schools across twelve districts in Pennsylvania, New York, and Alabama. During this time, participating teachers implemented the platform over a semester and researchers from *WriteGuide* used data mining, interviews, and direct observation to understand the software's on-the-ground usage. On the other hand, the company also continued to partner with testing companies like College Board to experiment with automated assessment on PSAT/SAT and AP exams, and with McGraw-Hill to pilot automated grading on tests in the Smarter Balanced Assessment Consortium – a leading standards-aligned state test provider. While teaching students to write is different from teaching them to write for standardized tests, these twin impulses gradually merged together as the platform evolved through conversations with educators and test-providers. By mid-2014, a technical report from *WriteGuide* named one its promising uses as 'predicting standardized test scores.' In other words, the software could be used to forecast students' scores which, in turn, would allow teachers to make 'early interventions for students, resulting in improved standardized assessment scores' (DOC6). It was during this pivot toward test-preparation that *WriteGuide* was acquired by *BeowulfEd*. *WriteGuide* was subsequently renamed to *Essay Helper*, and in early-2016 was launched as a feature integrated into *BeowulfEd's* K-16 userbase, while continuing to develop its partnerships with high-stakes testing companies.

Case study analysis

The rubric & state standards

Relationships with testing companies were instrumental in shaping the rubrics and standards used to produce the algorithm's training data. To generate aggregate data to direct students' revisions, training data is must organize writing into component skills, and sort them according to their relative quality. *Essay Helper* accomplishes this through rubrics that parse student work for elements of composition – claim and focus, or use of evidence – which are then scored along four tiers: emergent, developing, proficient, and advanced (Figure 2). Rather than inventing these categories anew, *Essay Helper*'s rubrics correlate with state standards and assessments. As its development documents state, 'To design our rubrics, we examined each state's learning objectives and focused on aligning criteria to standards' (DOC9, p. 6). Specifically, the platform structures its evaluations around Common Core State Standards (NGA/CCSSO, 2010) – the college- and career-readiness standards used to organize and assess learning in 42 states. While states and districts have, to date, struggled to implement these standards and align instruction accordingly (Polikoff 2015; Desimone et al. 2019), one promise of *Essay Helper* is the ability to automate this process. Using a machine-learning algorithm trained on data from based rubrics, *Essay Helper* allows schools to streamline implementation, mechanizing writing instruction so it is tightly aligned with standards.

Because this process is 'intelligent' – not just conditioning users to game the automated system, but identifying individual weaknesses for personalized improvement – the *Essay Helper* documentation calls its method 'inclusive' (DOC9). However, this inclusivity is structured by the platform's technical limits. While the algorithm is able to isolate and evaluate many users' competencies, it strains to do so for writers who fall outside the 'norm' of its aggregate training data. This is evinced in the platform's treatment of English learners. Early in *Essay Helper*'s development, an internal

	Claim and Focus
Advanced	The writer clearly introduces an arguable and specific claim or analysis based on the topic or text(s) and remains focused on supporting that claim throughout the essay.
Proficient	The writer clearly introduces a claim or analysis based on the topic or text(s) and stays focused on the claim throughout the essay.
Developing	The writer's claim or analysis is discernible, but it may not be clearly stated in an introduction. The writer may sometimes lose focus on the argument, instead summarizing the topic or text(s).
Emergent	The writer does not clearly make a claim or offer an analysis, or the claim is overly general or vague. The essay does not maintain a focus on an argument or the topic or text(s).

Figure 2. Definitions for each of the four tier scores.

memo specifically excludes non-native English speakers from its targeted userbase, saying, 'We are not particularly interested in building our tools for second-language learners. These students are fundamentally in need of a different type of feedback for improvement of skills compared to native speakers' (DOC4, p. 9). It is one thing for a company to acknowledge its limitations as a small start-up; however, this admission takes on new meaning when the platform is brought to scale as a resource for districts to align instruction with standards. Regardless of how 'inclusive' the platform's method of analyzing writing is, English learners are explicitly *excluded* from the support the platform offers. This is especially ironic given the focus in recent federal policy, like the Every Student Succeeds Act (ESSA), on improving support for English learners. With nearly 10 percent of U.S. students identifying as English-learners (NCES 2014), states are increasingly prioritizing language support in their reform efforts (|C-SAIL 2017a; 2017b). Even as *Essay Helper* is integrated to support standards-aligned writing instruction, its limitations are not orientated toward addressing the standards' larger interest in equity for English learners. As the platform documentation states, 'It's not where we're throwing our best efforts and attention in trying to grow' (DOC4, p. 9).

The sample of training data

Like any machine learning platform, *Essay Helper* relies on training data to calibrate its responses to human inputs – in this case, student-generated writing. The platform's documentation specifies its training data as 'a collection of essays that are written by students from the target population, in response to a [proposed] prompt' (DOC9, p. 6). To develop this dataset, *Essay Helper* staff and school partners (e.g., classroom teachers) create prompts, which are them assigned to a sample group of students. This process generates 300–500 300 example essays which serves as the corpus of training data (DOC9, pp. 4,6). Importantly, because '[e]ach prompt is associated with a rubric that is aligned to learning objectives for a specific genre of writing', sample essays that are produced from a proposed prompt are collected from students in grade appropriate classrooms in a locality (DOC9, p. 4). From there, essays are hand-scored by raters – teachers in the company's partner schools – according to the rubric. Student responses are assessed along several writing traits (e.g., clarity, organization) and scored on four tiers: (i.e., emergent, developing, proficient, and advanced) on a scale from 1 to 4 (DOC9, pp. 4,7; DOC10, p. 2072). *Essay Helper* then uses this information to construct an ordinal scoring model that can be used to evaluate future responses.

Essay Helper documentation asserts that these training data sets are representative of the target population to which the ordinal score model will be applied. That is, it suggests there should not be problems in generalizing from this sample data to the larger population who will use the platform. Even more, it infers that this training data will be representative of the diverse ways students might respond to or interpret a prompt. There is reason, however, to question this claim. Even if one accepts the premise that the sample data could encompass the full range of possible responses to the platform's prompts, those data are only 'representative' for that provisional instance of measurement. In other words, *Essay Helper* treats its training sets as fixed entities whose elements are unchanging. We would contend, by contrast, that once sample essays are collected, the in-process phenomena (i.e., student responses) have already moved, reconfigured, and changed. This is especially true in platform architectures like *Essay Helper*'s, where the algorithm itself is not adapting. The reflexivity of an autopoietic algorithm that learns/updates as it processes new information is, in theory, to account for a world of information that is in process of becoming.

The rubric used in constructing the training data surfaces another tension in the platform's design. As assessment tools created to ascertain whether students have achieved a specific outcome, rubrics are not principally concerned with providing the detailed, diagnostic feedback that *Essay Helper* purports to offer. The parent-company acknowledges as much in their documentation, saying, 'A frequent downside of many rubrics is that they fail to give actionable advice. For example … a score of 2/4 … doesn't necessarily help students who are trying to understand where they are and how to improve' (DOC9, p. 6). The documentation goes on, explaining that, before feedback can be given, essays must be grouped by predetermined criteria and ranked based on text characteristics. The irony, of course, is that rubric scores serve as the basis for providing essay feedback and these scores and the rubrics themselves are defined by state learning objectives, experts, and educators (DOC9, p. 6). *Essay Helper*'s use of rubrics, then, assumes that the writing process can be assessed fairly and that writing tasks can be objectively evaluated. Of course, such a stance elides the longer, discursive history of rubrics, which have worked to institutionalize particular ways of writing and knowing, and to reinscribe specific racialized processes of human becoming.

One further limitation, articulated in the *Essay Helper* documentation, is the platform's inability to account for writing that deviates from the expected task. Even as its developers claim the training data are representative of the full range of possible responses to a prompt, it acknowledges that this is based on an assumption that 'students will, broadly, bring the same types of information, background knowledge, and rhetorical style to an assignment' (DOC9, p. 8). By addressing this shortcoming, the company recognizes that the pedagogy of the platform presupposes particular kinds of student-users, which in turn, produce boundaries of acceptable practice.

On the sociopolitical formation of algorithmic reason

Following the collection and scoring of the training data, the creators of *Essay Helper* use two algorithms to build the platform's AI. These algorithms include Stanford CoreNLP for natural language processing and supervised learning ordinal logistic regression. Both of these algorithms work in concert to build a prediction model for the scoring of the essays on each criteria and to provide formative feedback.

Building the platform's prediction model necessitates natural language processing of the essays and a learning algorithm for score prediction. Stanford CoreNLP is used to discover and operationalize the feature space of the essays of the training data (DOC3). The features are based on words, paired collocations of adjacent words, parts of speech, and letters (not just for spelling but for shared word form such as 'collection' and 'section') (DOC3). Thus, the feature space of the essays could easily be in the thousands. Using the discovered features, the learning model can be trained, based on the analysis of the hand-scored essays in relation to the features, as model predictors. From 2013 to 2016, *Essay Helper* used the Weka Naive Bayes algorithm as the core learning algorithm for the platform. Beginning in early 2017, the company switched to the ordinal logistic regression (OLR) because it uses high-dimensional modeling techniques, and relaxes the constraint that model features should mimic human reasoning (DOC10). OLR estimates the conditional probabilities of an essay receiving a particular score given that it scores at least that high in relationship to the feature space of the essays (DOC10). By training the ordinal logistic regression algorithm on a training dataset of scored essays, *Essay Helper* is able to replace the costly and less efficient three-human scorer practices of yesteryear.

Using the hand-scored sample essays, the OLR model groups sample essays by rubric criterion score, analyzing them in relation to the feature space of the essays. This enables the algorithm to discover, extract, and compile a list of text features from sample essays that received that trait score (DOC9, pp. 4, 9). With the model calibrated on the training data, it is then able to predict scores on future student essays and to provide initial information for developing formative feedback. By analyzing the scores for each rubric in relation to the features, they can identify which features are more highly associated with rubric score levels. They are then able to provide feedback on essays portions that were estimated to be associated with lower or high scores on specific rubrics. As they state,

> We hypothesize that some writing characteristics—either content or style—are consistent across students at each skill level. If this is true, then some features will be very common among essays written by struggling students, and those same features will not appear in essays by the most skilled writers. The converse will also be true: … . (DOC9, p. 9)

Based on this hypothesis, they collaborate with educators and experts to develop the feedback the platform provides to student-writers. Of course, the full process involves more detail than we have space here to provide, but this description gives a general overview of how the platform is algorithmically designed.

Although this application of computational methods to develop a novel AI-based educational technology is empirically grounded, important theoretical considerations remain. The logistic function, for instance, while initially developed in the nineteenth century to study population growth, found uptake in 1920 when the term 'logistic' was reintroduced by biologist and eugenicist, Raymond Pearl and his associate, Lowell Reed. Pearl trained in statistics with Karl Pearson, the mathematician and eugenicist, and helped to developer of population studies. The logistic curve (aka Pearl curve) was among his major career achievements. For Pearl, the s-shaped curve captured a universal process of growth and the only thing that varied was the intercept, which was based on natural human differences. As Ramsden (2002) states 'Pearl's logistic curve represented all that was wrong with the biologist's attempt to study population dynamics, and moreover, epitomized the threat of biological imperialism and determinism to social science and social reform.'

Pearl's logistic curve was developed into the logistic regression model in the mid-twentieth century, most notably by Joseph Berkson for bioassay research. Berkson's development of logistic regression from Pearl and Reed's (1920) logistic function still made humanist assumptions of the liberal subject. This is specifically materialized in the analysis of a phenomena that is categorized on an ordinal scale, which essentializes human group differences that are further colonized by hierarchizing (i.e., ordinal) those differences. As a comparative method of analysis that necessitates identity and difference, logistic regression became one of the main methods for post-colonial analytics of raciality and the pathologizing of difference.

What consolidates the differentiating and hierarchizing process of logistic regression into a racializing assemblage is the sociopolitical constitution of the operationalizing of the criterion. As discussed above, the rubrics for hand-scoring essays for *Essay Helper* are defined based on Common Core State Standards. Thus, when the supervised learning OLS algorithm is calibrated using the training data of hand-scored sample essays by human experts, this is a critical process whereby the algorithm becomes sociogenically encoded and a racializing assemblage.

Goal-setting, iterability, & the biopolitics of revisioning

With *Essay Helper*'s sociogenic encoding – from standards-defined rubrics to the generation of training data to the calibrating of the algorithm – these elisions and reproductions of difference are, likewise, brought to scale. Where ESSA and college- and career-readiness standards were intended to bring equitable attention to special populations – specifically English learners, and students with disabilities – these same groups are among those least amenable to inclusion in *Essay Helper*'s training data, or to be supported by its personalized interventions. Even as the platform is ostensibly aligned to state standards, then, it is only so for those whose writing – and, perhaps, whose being – are legible to the procedural logic of the machine learning algorithm.

Crucially, this production of difference is not limited to the external markers of variation in language and ability, but also in the practice of writing itself. In the same way that the assemblage of training data congeals into an ideal user-subject – based on the sources of data collection: a white, middle-class, able-bodied, native English speaker – it also yields an ideal model of writing. Herein lies the algorithmic materialization of what Sylvia Wynter (2007) calls 'Western Man and the parameterizing of sociopolitical relations' into the protocological formations of the algorithm. This model, conditioned by the competencies valued in the Common Core standards, in turn, becomes the form against which all subsequent student writing in the platform is measured, becoming what da Silva (2001) has characterized as an analytics of raciality, a comparative analytics that privileges particular ways of human becoming over and against all other processes of becoming. The iterative process of revision, as adjudicated by the platform, is not so much an emergent response to a communicative act than it is a re-direction toward the predetermined shape of the ideal written form. Like Michelangelo's block of marble, revision becomes a subtractive task of chiseling away at one's work to form it into the shape it was always meant to take. The *Essay Helper* documentation suggests that such an approach is tied to research on the writing-process, saying, 'Writing researchers view task-based writing as a cyclic process focusing on idea generation and converting ideas into words iteratively' (DOC6, p. 8). However, there is a marked difference between the open-ended iteration of allowing writing to unfold in response to emergent thinking of the writer or the needs of their real or imagined audiences, and the circumscribed iteration of reconfiguring ones work to better fit the contours of an aggregate dataset. If the term 'revision' itself means, literally, to see again or anew, the latter suggests an inherent telos in such a process – it is the seeing anew of a puzzle-doer recursively consulting the image on the puzzle-box, not that of author returning to their words to make them more lucid, descriptive, or forceful for their readers.

Revision's emphasis on 'seeing anew' suggests an iterability in the practice of writing. As Derrida ([1972] 1982) argues, what makes language, speech acts, or social practices effective, intelligible, and communicable is repetition. This is not repetition in a linear sense, but rather, one based on iterability. Building on the Sanskrit meaning of the prefix *iter-* as 'other,' he conceptualizes iterability as repetition with alterity; that is, repetition with differentiation and nonuniform sameness. Thus, iterability in the revision process is ultimately about alterity, differentiation, and nonuniform sameness in written expression. In the context of the platform, while the content of the iterability of revision is still differentiated and differed, the circumscribed structure of expression is not. As discussed earlier, writing is an embodied and sociomaterial process of relational ontologies that assumes the body to be constantly intra-acting and reconfiguring with other ontologies. Thus, iterability is not just a human process but a more-than-human performative process as well. In fact, the iterability of the algorithmic performative acts of *Essay Helper* reconfigures the sociomaterial practice of writing into a becoming-sociotechnical practice of writing that is entangled as an assemblage with the platform.

This ironically raises questions and even challenges traditional individualist notions of authorship. In addition, we speculate that the affect of the circumscribed structure of writing via algorithmic scoring and feedback over time will begin to preconsciously shape neurocognitive structures of users ways of thinking, repressing or excluding other previously-conditioned modes of thinking and structures of written expression. That said, we can also imagine forms of subversive *play* that users might take up, over time, within the circumscribed structure of the learning analytics platform. It is such intervals and processes of potentiality that make us wonder about alternative futures.

Alternative futures of learning analytics

Through this case study analysis of *Essay Helper,* we have considered particular processes that may produce a racialized-becoming of the platform. With that, we also want to point toward what we currently see as potentialities for alternative futures.

As a path toward addressing neoliberal forces directly in the platform, a decoupling of *Essay Helper* from state standards would be necessary. As long as standards condition the rubric, and by extension, the training data used to automate formative feedback, *Essay Helper* will retain a circumscribed telos bound up with local and national accountability measures. Demonstrating competence in standards is only one purpose for which students might write. It would be possible, in other words, to imagine alternate rubrics that might shape the training data to provide non-evaluative feedback on more expansive forms of writing, including those that are not tested. For instance, the present configuration of the platform would strain to accommodate genres of writing outside of expository prose; however, if testing was not the principal concern, it would be possible to hone algorithmic responses to poetry or narrative writing. This has been a subject of experimentation in corners of the digital humanities and computational poetics (Montfort 2016), but perhaps learning analytics might provide pathways for these modes of expression to find room in traditional K-12 classrooms as well.

Relatedly, decoupling from the standards might also open pathways for once-abandoned platform features to be revived. Early in *Essay Helper*'s development, for instance, there was a focus on peer-review, which died away once funding was secured to develop automated assessment features. However, without the pressure to scaffold student writing to the test, the platform's capacities might be re-directed toward facilitating peer-to-peer reading and response. Where in its present form, writers address an abstract, aggregated 'reader' – conditioned by the standards, rubrics, and training data – an alternate version might, instead, provide ways to enhance the forms of feedback that are generated locally, by other students in the classroom.

We might also imagine approaches of computational reason other-wise; or, approaches that may be more informed by a black radical tradition. *Essay Helper*, like many learning analytics platforms, deploys a non-adaptive predictive model that does not actively learn as it processes new data. What would happen if the platform was actively learning? That is to say, how might the model parameters become reconfigured as a result of processing new essays? One could argue that the errors, the indeterminacies, and the incomputables the algorithm will process would likely include writings from precarious or marginalized processes of becoming. Might the learning algorithm begin to process other-wise; that is, begin to take on a mode of thought that is beyond that which was humanly inscribed into the rubric scores (Dixon-Román 2016; Parisi 2013)? Given the backwards engineering design of the platform, this could be quite difficult if not prohibitive, yet the platform could be designed other-wise in order to enable such an adaptive learning configuration. A more radical approach to develop algorithmic thinking other-wise is to train the algorithms to privilege nondominant processes of becoming in the scoring rubric. In other words, the rubrics would not be informed by policy standards or white colonial logics but on precarious and marginalized ways of writing and knowing. This would not only be a computationally-embedded critique of Western culture, but might also enable a shift in the association between blackness and brownness with technology.

While our speculative inquiry on learning analytics platforms has yielded considerable insights, many more questions remain unanswered. One question that is of great importance is the social composition of users. A simple internet search will return a near-endless list of educational technology solutions and learning analytics platforms for use in schools and classrooms. Less is known, however, about the users of these tools. For example, are certain schools more likely to adopt such a tool? What are the circumstances that might lead a school to adopt a learning analytics solution like *Essay Helper*? A related question concerns whether a tool like *Essay Helper* is materially different from the current mode of practice? To address this inquiry, one would not only need insight into how students interact with the platform but also whether teachers use the platform as a supplementary teaching tool in conjunction with more conventional methods of instruction or if the adoption of such a tool precedes a decline in teaching and teachers. Another question is to what extent learning analytics platforms support student learning outcomes such as standardized test performance? Such a line of inquiry would provide useful information about the efficacy of computerized literacy interventions.

The promises of AI in education, broadly, and *Essay Helper*, in particular, are tremendous; yet, there remains much to learn regarding the ontologies of these computational systems. Our speculative inquiry here suggests that there are multiple processes entangled in the becoming of the sociotechnical assemblage, and racializing forces are one of them. While assemblages of sociopolitical relations are imbricated and inseparable, we must find ways of thinking and living blackness other-wise; a redefining of blackness as a subject with critical, affirming, and intellective qualities that is in no way reduced to the 'flesh'. This blackness other-wise needs to be a radical onto-epistemological shift materially, discursively, and computationally, including an AI-other-wise in education.

Notes

1. While AI refers to theories and approaches to produce computer generated tasks of human intelligence, machine learning is a subset of AI that extracts information from data patterns in order to enable an automated process of algorithmic decision making. We use these terms interchangeably throughout the paper.
2. Per agreement, we used pseudonyms (e.g., BeowulfEd, Essay Helper, & WriteGuide) for the name of the educational technology company and its learning analytics platform in order to maintain anonymity.

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