Structural Justice in Student Analytics, or, the Silence of the Bunnies

Jeffrey Alan Johnson, Ph.D.
Interim Director
Institutional Effectiveness and Planning
Utah Valley University

Presented at the 2017 Digital Sociology Mini-Conference
Eastern Sociological Society Annual Meeting
Philadelphia – February 24, 2017

800 West University Parkway,
Orem, Utah 84058
jeffrey.johnson@uvu.edu | @the_other_jeff

Structural Justice in Student Analytics, or, the Silence of the Bunnies

The explosion of student learning and behavioral analytics raises deep questions about whether it can be done within a meaningful frame of information justice. These questions that came to the forefront of public discourse in 2016 when Mount St. Mary's University President Simon Newman described using predictive student analytics to weed out students unlikely to be retained as a way to "drown the bunnies . . . put a Glock to their heads" (Svrluga, 2016a). Using the Mount St. Mary's University incident as a touchstone case and generalizing that to a broadly applicable model of predictive student analytics, this paper suggests that these concerns can best be understood within a framework of structural justice. The structural concept of justice articulated by Young (1990) finds justice rooted in aspects of social structure that promote or impede self-development and self-determination. I examine three types of structures: showing that organizational, politico-economic, and knowledge structures all pose significant challenges to justice in predictive student analytics. This approach is able to determine that "drown the bunnies" models are categorically disrespectful of self-development and in most cases permit little self-determination for students, demonstrating that information justice is at least equally, if not primarily, a question of structural justice.

BUNNIES, GLOCKS, AND ANALYTICS

Predictive student analytics are algorithmic systems that use data from student behavior and performance to generate individual predictions for student outcomes.[1] Nominally, the purpose of student academics is to promote student success. But the case of Mount St. Mary's University[2] shows just how contentious definitions of student success can be, and how such definitions are critical to understanding and using student analytics. Mount St. Mary's University thus provides a valuable case study of how predictive student analytics can lead to fundamental information injustices in higher education.

The Mount St. Mary's University Case

Mount Saint Mary's University attempted to use predictive student analytics to improve the university's first-to-second year retention rates (Schisler & Golden, 2016). The university had a 66% graduation rate for its 2009 cohort of first-time, full-time entering students, and 78% of its 2014 cohort returned in 2015. Both rates are well above the national average for four-year institutions but commonly exceeded by private liberal arts colleges (Jaschnik, 2016a). Those rates are based on standards used in the federal Integrated Postsecondary Education Data System (IPEDS), which identifies cohorts based on the institution's fall census date. The cohorts, with some generally minor adjustments, are the denominator for graduation and retention rates. Students who enroll as first-

[1] For the purpose of this paper I will use the terms "predictive analytics" to refer to predictive methods generally, and "predictive student analytics" or simply "student analytics" to refer to such methods used in educational contexts. The term this includes but is not limited to the narrower concept of "learning analytics," which describes the use of such methods based on primarily academic behavioral and performance data to predict future academic performance and individuate course and program content.

[2] There are several higher education institutions in the United States with similar names. Mount Saint Mary's University, the object of this case study, is in Emmitsburg, Maryland. It should not be confused with Mount St. Mary's College in Los Angeles, or Mount Saint Mary College in Newburgh, New York.

time, full-time students but withdraw from an institution before the census date are not included in the cohort. In Mount Saint Mary's University's case, the census date was initially September 25, approximately one month after orientation for entering students (Schisler & Golden, 2016).

Emails obtained by *The Mountain Echo*, Mount St. Mary's University's student newspaper, show that, at the suggestion of then-president and private equity investor Simon Newman, Mount Saint Mary's University instituted a locally developed survey intended, ostensibly, to develop better metrics for student analytics to be administered at the student orientation. While the instructions for the survey suggested it was purely informational and designed to "help you [the student] discover more about yourself" the emails revealed that the intent of the administration was to dismiss 20 to 25 students before the IPEDS reporting date, based in part on the survey results:

> Newman's email continued: "My short term goal is to have 20-25 people leave by the 25th [of Sep.]. This one thing will boost our retention 4-5%. A larger committee or group needs to work on the details but I think you get the objective."

Emails from other campus leaders make clear that the use of the survey to dismiss students was made unilaterally by Newman in the face of strong opposition from those leaders, characterizing the risk that some of those dismissed might succeed as "some collateral damage." Associate Provost Leona Sevick stated that the plan would contradict catalog standards for dismissing students. In response to *The Mountain Echo's* investigation, chairman of the university's Board of Trustees John E. Coyne III characterized the program as part of "the Mount's efforts to improve student retention and to intervene early on to assure that incoming students have every opportunity to succeed at our university," and in December Newman stated in an email to the faculty, "It has never been a goal to 'kick out' first year students because they were not doing well". The plan failed to come to fruition as some campus leaders stalled the decision of whom to dismiss until after the IPEDS deadline, which the university extended by one week in an effort to identify students to dismiss (Schisler & Golden, 2016).

The headline-grabbing aspect of the controversy was neither the intent nor the process; rather, it was a conversation between Newman and other campus officials that elevated the case to international news. Newman requested that the director of the university's first-year student symposium, Dr. Greg Murry, provide Newman with a list of students who were unlikely to return. In response to Murry's objections and in the presence of another faculty member, Newman said, "This is hard for you because you think of the students as cuddly bunnies, but you can't. You just have to drown the bunnies…put a Glock to their heads" (Schisler & Golden, 2016). The exceptionally violent metaphor shocked the higher education community, generating extensive coverage based on *The Mountain Echo's* reporting. Both Newman and the Board of Trustees confirmed Newman's statement. The board characterized Newman's "drown the bunnies" comment as an "unfortunate metaphor" (Lee, 2016), and Newman stated that he regretted the language but not the intent of his statement (Svrluga, 2016a).

The controversy was aggravated by university efforts to blame the student journalists for revealing the information and then punish faculty for their opposition. Coyne initially dismissed the story as "the product of a disgruntled employee and the creative and destructive imagination of a student being spoon fed his information" (Schisler & Golden, 2016). Backed by the Trustees, Newman terminated the paper's faculty advisor and a tenured philosophy professor and demoted the university's provost and a dean for "disloyalty" (though they were reinstated three days later). The controversy ultimately provoked an unsustainable backlash, as parents and alumni threatened to pull students and donations from the university and the university's accreditor, the Middle States Commission on Higher Education, requested an ad hoc report on implications of the process for accreditation (Jaschnik, 2016b). In the face of growing opposition, Newman eventually resigned (Joseph & McPhate, 2016).

Sensationalism aside, however, it is the process by which Mount St. Mary's College intended to dismiss students that raises questions of information justice in this case. The survey that Mount St. Mary's University used (see Table 1) was obtained and made public by *The Washington Post* (Svrluga, 2016b). It consists of approximately 14 sections and 110 individual responses. It was developed locally but consisted of both locally developed individual items and items taken from a hodgepodge of psychometric instruments. Broadly, the survey addresses three topics: courses and programs, non-cognitive student characteristics, and student activities. Following the introduction, there is a section discussing possible new courses and programs that the university might offer. There is a wide range of programs listed, from philosophy, politics, and economics to civil engineering. Students were asked to rate their interest in the course or program, and were offered an option expressing a willingness to pay "a small premium" to enroll in it. The bulk of the survey focuses on non-cognitive characteristics of students. This includes sections on both resilience and grit, personality inventories, sections about religious beliefs, and a section evaluating students for clinical depression. Most of these sections are abridged versions of established—in some cases,

Section	Content	Items
1	Introduction	0
2	New courses and programs	12
3	Internal-External Locus of Control Scale (Rotter, 1966)	5
4	Life Events	8
5	Academic Habits	12
6	Center for Epidemiologic Studies Depression Scale (Radloff, 1977)	10
7	Connor-Davidson Resilience Scale (Connor & Davidson, 2003)	5
8	Goz Lab Ten Item Personality Measure (Gosling et al., 2003)	10
9	Delaying Gratification Inventory (Hoerger et al., 2011)	10
10	College Students Beliefs and Values Survey (Astin et al., 2010)	3
11	Interpersonal Reactivity Index (Davis, 1983)	5
12	Short Grit Scale (Duckworth & Quinn, 2009)	8
13	Miscellaneous Items	11
14	Extracurricular Activities	12

Table 1: Mount St. Mary's University Class of 2019 Survey Structure

dated—psychometric instruments. The final section requests information on preferred activities (Mount St. Mary's University, 2016).

It is clear that the use of the survey to identify students to be dismissed was either contrary to its designed intent or to deliberately deceptive. The introduction states:

> We firmly believe that the SAT and ACT exams, and even a GPA score, do not effectively value the potential of anyone. At The Mount, we look beyond these simple numbers and seek to understand what motivates each student, as well as understand what factors may be holding each student back from performing at his or her best. . . . We will ask you some questions about yourself that we would like you to answer as honestly as possible. There are no wrong answers. . . . We believe everyone here has potential to become someone way beyond what you may think possible right now. (Mount St. Mary's University, 2016)

The appeal to self-development and support, and the claim that there are no wrong answers, is inconsistent with the aim of using the survey to identify students who will be discouraged from continuing their educations at the university. Far from becoming "someone way beyond what you may think possible right now," the survey—and much of its underlying psychometrics, designed to measure personality traits—assumes that the information on the survey represents consistent and stable aspects of students' character that are unlikely to change over the course of an academic career and are thus determinative of their success at Mount St. Mary's University.

Many in the administration at Mount St. Mary's University were well aware of and deeply concerned about the ethics of the "drown the bunnies" approach, and especially the survey. Dean Josh Hochschild, one of those involved in the email exchange obtained by *The Mountain Echo*, called the process "deeply disturbing," "highly intrusive and misleadingly framed," and "unethical," asking, "How can we in good conscience administer this?" Associate Provost Leona Sevick shared his concerns, noting that the dismissal process likely violated university policy stated in the catalog. Other university leaders were also cited in the article as voicing strong ethical objections. Nonetheless, Newman moved forward with the intent to dismiss students in spite of opposition, even pushing back the IPEDS reporting date (a move of dubious legality itself). The ethical objections were ineffective; ultimately the process was thwarted not by a conscious decision to do what was right but rather by stalling beyond the IPEDS deadline: Murry, the director of the first-year symposium, failed to provide the names of students to be dismissed, saying "We simply ran out the clock." (Schisler & Golden, 2016)

A Generalized "Drown the Bunnies" Model

How the survey was to be used to identify the students who were not likely to be retained to their second year is unclear, and Newman's comment that "A larger committee or group needs to work on the details" at least suggests that there was never a concrete methodology leading from data to intervention. While a few of the source instruments were designed specifically for higher education (Astin, Astin, & Lindholm, 2010) or measure constructs that have recognized applications in education (Connor & Davidson, 2003; Duckworth & Quinn, 2009; Hoerger, Quirk, & Weed, 2011), many of the instruments were designed for clinical use (Connor & Davidson, 2003; Davis, 1983; Gosling, Rentfrow, & Swann, 2003; Radloff, 1977; Rotter, 1966) and do not appear to have any established connection to educational settings. The use of the individual items frequently invalidates the source instruments, which are designed to operate as multiple-item indices (Astin et al., 2010; Connor & Davidson, 2003; Davis, 1983; Hoerger et al., 2011; Rotter, 1966). There is no evidence of any effort by the university to test validity or reliability, either of the abridged instruments as measures of the constructs the source instruments intended to measure, or of their association with each other as an overall measure of the likelihood of academic success. And the use of questions about mental health and learning disabilities suggests serious civil rights concerns as well as responsibilities to ensure that students whose responses indicate, for instance, major depressive disorder receive appropriate mental health care. Reporting does suggest that the intent was to use the survey results in conjunction with academic performance information from the first month of classes (Schisler & Golden, 2016). Absent a model that could predict how responses are associated with outcomes, the administration would be making marginally educated guesses about which students to dismiss.

While Mount St. Mary's University appeared to lack such a model, such models are increasingly available through predictive student analytics. Austin Peay State University pioneered the use of predictive student analytics through Degree Compass, a course recommendation system. Degree Compass uses student performance data from previous courses and recommends courses that would maximize students' GPA and thus their likelihood of maintaining scholarships and of graduating (Parry, 2012):

> Inspired by recommendation systems implemented by companies such as Netflix, Amazon, and Pandora, Degree Compass successfully pairs current students with the courses that best fit their talents and program of study for upcoming semesters. The model combines hundreds of thousands of past students' grades with each particular student's transcript to make individualized recommendations. (Denley, 2013)

The system works in part by predicting student performance in courses that the student might take, based on the performance of similar students in the past in addition to—or in the absence of—data on the student's own performance. While its stated purpose is to help students select courses that will lead to timely completion of the programs, it touts a 92% accuracy rate in predicting whether a student will receive a C grade or better in a course; Denley notes that completion success is a "hope" rather than an evidentiary claim. Following development support from the Bill and Melinda Gates Foundation, Degree Compass was acquired by learning management system vendor Desire2Learn, commercializing the product for use at any higher education institution (Denley, 2013). It thus has the capability of predicting student success even for entering students who have no track record of performance, the kind of prediction that Newman intended to join to the survey results.

The survey and academic data used by Mount St. Mary's University are also representative of recent approaches using predictive student analytics to "triage" students for support resources.

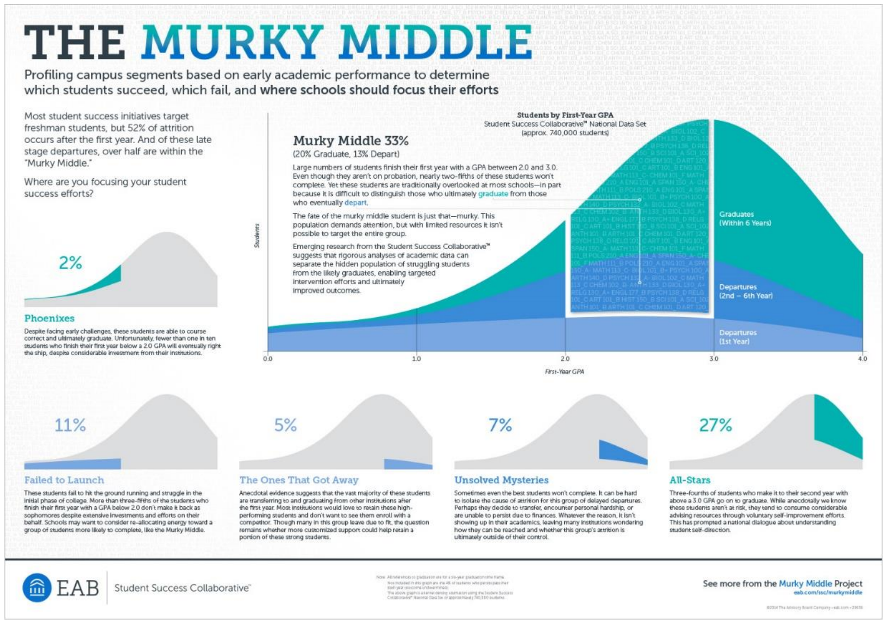

Figure 1: A triage approach to student support. (EAB Student Success Collaborative, 2015)

Essential to nearly all triage models, whether in their origin in battlefield medicine or as incarnated in in predictive student analytics for higher education, is the existence of three basic categories: those needing immediate care for a positive outcome, those who will see a positive outcome even without immediate care, and those who are beyond care. Commercial providers such as EAB (EAB Student Success Collaborative, 2015) argue that predictive analytics can support student success by allowing institutions to focus their efforts on the students for whom support will make a difference, noting that the top third of students are likely to succeed without support, and the bottom third are unlikely to succeed even with support. For the latter group, EAB suggests that schools "consider re-allocating energy toward a group of students more likely to complete" (see Figure 1). To do this organically, Mouth St. Mary's University would need to not only survey the class at entry but wait until students returned in their second year to build a model of retention. The survey this could not be used to predict retention of the class of 2019, the first to take the survey, but it would allow the university to predict the outcomes of subsequent classes, especially combining the pre-enrollment non-cognitive data with past student performance data along the lines of the methods used by Degree Compass.

While the specifics of Mount St. Mary's University are certainly problematic, the importance of the case for information justice in higher education comes in the context of initiatives like the EAB Student Success Collaborative and Degree Compass. This combination of broad collection of academic and non-cognitive data, predictive analytics methods, and triage-driven intervention intended to directly influence key quantitative indicators of success is now the state of the art in student services for retention and completion. Many of its characteristics can be seen in applications of predictive analytics in other areas such as criminal justice, where modelling identifies defendants who have the highest likelihood of failing to appear in court or of offending again and sets higher bail amounts, longer sentences, or recommends against parole, in some cases effectively denying bail or imposing life sentences for relatively minor crimes (Christin, Rosenblat, & boyd, 2015). This represents a significant new challenge in higher education management, especially from the perspective of meeting universities' responsibilities to students, and is a major area of application for information justice. In honor of former President Newman, I call this combination the "drown the bunnies" model.

STRUCTURAL JUSTICE

While many ethical issues have been raised in this case, there is a deeper challenge for information justice. At Mount St. Mary's University, knowledge of what is ethical—clearly present in abundance among everyone involved other than Newman—was insufficient by itself to produce a just outcome. This raises a consideration that ethics, with its focus on the justification of individual action, is poorly suited to engage. The decisive factor at Mount St. Mary's University was the balance of political power: the authority of the university president and the inherent gaps in the principal-agent relationship between him and his employees. This reflects fundamentally a changed conception of the terrain of student analytics: a movement from pedagogy to politics. We think of educational institutions as rather far removed from such questions, especially when considering questions of pedagogy. But it is easy to overlook that the actors driving the adoption of student analytics are rarely instructors; most commonly a coalition of administrators and vendors introduce analytics process to the institution, and then address use by instructors as seeking "buy-in" (implicitly, to a *fait accompli*) from faculty. This should encourage the view that predictive student analytics is a management process as much as an instructional or student support one. It is thus necessary to examine not only the myriad ethical considerations presented by "drown the bunnies" models but also these political relationships from the perspective of a coherent conception of justice itself.

Rawls holds that justice is "the first virtue of *social institutions*" (2005, p. 3, emphasis added), most commonly of political institutions associated with the nation-state. Political philosophers have taken two approaches to justice. The most common, distributive justice, considers the social institutions and practices of a community (which would include, for many philosophers, voluntary associational relationships like higher education institutions) to be just if they reflect a just distribution of material and moral goods (for example, rights, liberties, or authority). There are myriad theories of distributive justice varying both by focus on processes versus outcomes and by standards for determining a just distribution of goods.

Young (1990), however, argues that distributive approaches are inadequate when the question is one of relationships among people or groups rather than material goods. Such approaches fail to understand how social institutions shape "action, decisions about action, and provision of the means to develop and exercise capacities (1990, p. 16)"; these are as much a consequence of structural factors as they are distributions of material and moral goods. Instead, Young presents a structural theory of justice: a society is just to the extent that social structures and relationships facilitate both the capacity to develop and exercise one's human capacities (that is, self-development) and supports one's participation in determining their actions (self-determination). Likewise, injustice has two corresponding forms. The denial of self-development is oppression; that of self-determination, domination. These conditions are not matters of either distribution or of individual ethics; they are part of the social structure:

> Oppression in this sense is structural, rather than the result of a few people's choices or policies. Its causes are embedded in unquestioned norms, habits, and symbols, in the assumptions underlying institutional rules and the collective consequences of following those rules. . . . In this extended structural sense oppression refers to the vast and deep injustices some groups suffer as a consequence of often unconscious assumptions and reactions of well-meaning people in ordinary interactions, media and cultural stereotypes, and structural features of bureaucratic hierarchies and market mechanisms—in short, the normal processes of everyday life. We cannot eliminate this structural oppression by getting rid of the rulers or making some new laws, because oppressions are systematically reproduced in major economic, political, and cultural institutions. (Young, 1990, p. 41)

Young uses this framework to understand and articulate the claims of injustice posed by various emancipatory social movements, suggesting that it is a particularly valuable approach for information justice.

Simultaneously protecting both self-development and self-determination is difficult. There are always some constraints on self-development and self-determination; especially in education, structural justice is constrained by the sometimes inherent conflict between the two. Most pedagogical approaches assume that learning requires systematic guidance and thus limit students' self-determination in order to further their capacities for self-development. Moreover, the two considerations are mutually constructive. Self-development begets self-determination, and vice versa, and both dimensions of structural justice create the self as they reflect it. Perrotta and Williamson show that "Methods used for the classification and measurement of online education are partially involved in the creation of the realities they claim to measure (2016, p. 2)." Students exist as students in part because we choose to measure them as students; measuring them as students creates the role of student discussed above as well as reflects a role that students bring themselves. At many institutions, for instance, continuing education students are not included in reported enrollment data. All institutions exclude non-degree-seeking students when reporting graduation rates to the federal IPEDS data system, but they report such students in the IPEDS enrollment survey. These decisions shape who institutions think of—and plan for—when they refer to their students as well as which attendees at the institution think of themselves as students. The decision of whom to count as students plays a substantial role in creating the identity of "student." As such, predictive student analytics, like all educational practices, do not just constrain or facilitate self-development or self-determination; they in fact contribute to the creation of the selves that seek development and determination.

Structural justice is thus a far more complex form of justice than distributive justice, matching the complexity of the underlying relationships it seeks to evaluate. This is why most structural approaches to justice argue not for a maximal distribution of self-development and self-determination but rather against social structures that limit these, and see justice as a political rather than rational process, as the outcome of a negotiation among conflicting groups that itself respects self-development and self-determination rather than the result of an algorithmic determination (as, for instance, Rawls' two principles of justice would have one perform). Just as being governed by the winner of a free and fair election who respects the right of opposition and the rule of law does not deprive one of one's self-determination, neither does a student who willing submits to the tutelage of an expert who is committed to that student's self-development do so. It is the capacity of the student to self-determine that recognizing the expertise of the teacher is the best path toward the student's own self-development, and their participation in institutional decisions that will exercise students' capacities for self-determine collectively (e.g., by making "all students shalt" policies), that enables a just relationship between teacher and student. Likewise, that exercise of self-determination requires a prerequisite level of self-development. This interplay is best captured by interactions through social institutions that respect the self-determination and self-development of all, that is, by political processes.

The concept of justice being a structural condition (or at least of having a structural dimension as a major component) that must be addressed through political processes shows why ethical approaches alone are unlikely to resolve concerns about the "drown the bunnies" model: the model—indeed all models—consists not just of individual practices that should be proscribed or mandated by ethical "law" (a law that lacks sanction, one notes), but also of capacities and concepts embedded in the institutional conditions of the university. If those processes do not respect self-development and self-determination, no amount of ethical reasoning will be effective, as we saw in the Mount St. Mary's University case. The key to sound predictive student analytics, then, is attention to the structural conditions in them that determine the extent to which student analytics supports the students' self-development and self-determination. The structural determinants of the Mount St. Mary's University case, directions characteristic of most instances of predictive student analytics, take many different forms.

Organizational Structures

The organizational authority structure of the university is the most readily apparent structure that influences predictive student analytics. The decisions about how to implement student analytics take place in organizations. The most obvious aspect of this is the organizational hierarchies of the university. When discussing justice in student analytics, there is a tendency to focus immediately on the expected intervention, which draws attention to the intent and competence of actors and the organizational roles that define those actors. Simon Newman's beliefs about the best way to manage student retention were irrelevant to the fortunes of Mount St. Mary's University students until he became President Simon Newman and could translate those beliefs into intentions and institutional actions. And they remained relevant only as long as he had the backing of other organizational structures (the Board of Trustees), who in turn could provide that support only as long as they were supported by empowered stakeholders such as donors who could vote with their pocketbooks and students who could vote with their feet.

Newman's demand that the university dismiss students unlikely to be retained reflected his (perceived) position of authority in the institution, a perception informed by a view of the university as a business organization. As president he acted as if he had full authority over the institution and was responsible for maximizing return on investment, as he would in the private equity firms from which he came to Mount St. Mary's university. We see this not only in the demand that the survey be used for this purpose without informing students but also in his disregard for institutional policies regarding dismissal procedures and in his firing of faculty members for disloyalty. This left students with neither the opportunity to participate in the decision (either directly or through the faculty members who were voicing the students' interests) nor the ability to make an informed decision about participation. This domination would have led to oppression of at least the 20 to 25 students Newman intended to dismiss, not just in that they were denied the educational opportunity at Mount St. Mary's University but that they were denied so in a way that prevented them from pursuing other educational opportunities. Had the students had meaningful input, the university might well have seen the virtue of using student analytics in the admissions process rather than after students arrived, a solution many institutions and commercial analytics vendors are now touting.

And yet, even with Newman's assertion of absolute authority backed by the Board of Trustees, the president did not get his way. Organizational hierarchies are more complex than might appear. Newman made the assumption of a bureaucratic hierarchy working toward the accomplishment of a monistic, self-interested aim characteristic of the business world. Failing to question that norm may well have prevented him from understanding the other norms at work in the university, especially those of shared governance and responsibility to serve the students rather than the university. These norms empowered the faculty and other senior administrators to oppose Newman through the organizational authorities, protections, and relationships created by shared governance principles. Tenured faculty members received a notice of termination but were ultimately not terminated in part because of the legal protections the university's tenure process gave them. Administrators lost their administrative positons, which at many institutions are held at the pleasure of a top-level institutional leader, but tenure protected their faculty positions. Those protections enabled resistance as much as the authorities of their positions. And that resistance allowed opponents of the process to take advantage of the inherent gaps that exist in any system of bureaucratic authority, creating slippage between nominal principles and nominal agents (See, e.g., Kassim & Menon, 2003) that thwarted Newman's aims.

Ultimately, the "drown the bunnies" model is an exercise of managerial authority. Student analytics is a management process, one that affirms the authority of the institution—a social structure in which the student participates—over the student. Student analytics first makes students "legible" (See Scott, 1998) to the institution so that the administration can describe and understand the environment within which the institution acts: The Mount St. Mary's University survey identifies different types of students who have varying needs and will likely follow different paths in their academic careers. Analytics then makes the behavior of the student (at least appear to be) predictable to the institution: Degree Compass generates a predicted likelihood of a student passing a course in order to generate a recommendation. And finally analytics is used to control the environment itself by providing a basis for reliable action: EAB targets student support resources on the "Murky Middle" so that institutions can maximize their retention and graduation rates. All of these efforts ultimately make the institution's actions more reliable and more likely to achieve their ends, enhancing its capacity to act on—thus to exercise authority over—its students. This is a significant shift in self-determination, and to the extent that it is driven by institutional rather than student interests, a significant limitation on students' self-development.

Political and Economic Structures

Bureaucratic hierarchy is by no means the only organizational structure that shapes the justice of "drown the bunnies" models. The institution, the state, and the political economy all structure the content and use of student analytics. Analytics processes may use hundreds of variables, but institutions and the state have chosen what variables will be available to the system by choosing what data to collect, how to store it, and what to make public. This puts emphasis on certain highly visible data points and may prevent analysis of others. Within institutions, these data structures often leave students entirely uninvolved or only include often unrepresentative student organizations. This is unquestionably a major factor in the Mount St. Mary's University case. Newman appears to have been driven solely by the desire to improve the federally reported first-year retention rate, and pursued a method that did so only because of the federal formula for identifying the cohort. If the cohort were defined differently—for instance, if it included all newly admitted students who enrolled before the first day of classes—Newman's approach would have done nothing to change the retention rate; every student who took the survey would have been included in the cohort. Had Newman been president of a public university with an early census date he would not have had time to dismiss students or the ability to push the institutional reporting date back as he did. And had he been obligated to consider input from students, parents, or other stakeholders who ultimately opposed his process he might have had to consider whether the better response would be to develop an institutional narrative on the weaknesses of the retention rate for the university, as many institutions do for the highly unrepresentative IPEDS graduation rate. The federal policy context, especially to the extent that it is influenced by non-democratic factors such as industry lobbying and policy biases toward "traditional students from traditional families attending traditional institutions"

(Institutional Effectiveness and Planning, 2015) rather than the contemporary non-traditional student majority, incentivizes institutions to undermine student self-determination.

Newman's efforts to shape retention rates also followed major pushes by the Obama administration to enact a ratings process for institutions (first the Postsecondary Institution Ratings System and then a revamped College Scorecard) that gave high priority to retention rates and thus increased pressure on institutions to report higher rates. In this respect, Mount St. Mary's University is typical of the commercial analytics vendors being used as part of "drown the bunnies" models, whose products are usually designed to support students included in the IPEDS graduation rate cohort and not retention of new students generally. Students, in the face of pressures on institutions that are to be met with commercial analytics products, serve as a means to an end that is in the institution's interest, a resource to be used to shape the retention rate that the institution reports, rather than as the end that the retention rate measures: There is all the difference in the world between improving student retention and improving IPEDS retention rates, and the focus on the latter at the expense of students' interests—or of defining the latter as exclusively the former—is a form of structural oppression.

Beyond the institutions themselves the political economy of predictive analytics both situates systems within intellectual property law that makes them "black boxes" opaque to examination and, as development is often a commercialization of one institution's system, makes generalizability an assumption rather than demonstrating it: Political and economic power thus reinforce scientism. The failure to examine these structures makes an ethics-only approach likely to fail. For example, although Boon (2016) recommends sharing data with students to empower them in informed, data-driven decision-making and involves students directly in decisions about student analytics, much of the student involvement in her model takes place in an environment that has already been strongly constrained by institutional decisions and systems. Students have a modicum of autonomy within a much deeper system of constraint that makes "informed decision making" much more a matter of institutionally driven disciplinarity.

This was not an issue in the Mount St. Mary's University case, as they did not reach the point of using commercial student analytics packages. But it must be a serious concern for the "drown the bunnies" model more broadly. Austin Peay State University commercialized Degree Compass, first expanding its use to other institutions in Tennessee—demonstrating it at "schools with a broad cross-section of curricular structures and student populations" where "their data offer us an opportunity to further refine the predictive modeling"—and then selling it to Desire2Learn where it could be integrated into its learning management system and connect to institutional data. While developers tout Degree Compass as using "modeling techniques could calibrate themselves to differing institutional settings and student populations" (Denley, 2013). But it does not provide access to the model itself. A competing product in use at another institution is structured so that retention predictions can only be accessed individually, preventing the kind of bulk data extraction necessary for the institution to test the accuracy of its predictions for the campus. The institution's representatives were told this was to prevent reverse engineering the algorithm, which was protected intellectual property. Under such conditions institutions—and the students on whom their policies act—are unable to interrogate these systems' algorithms or results and understand the basis of its recommendations not because of technical limitations, but because of how a profit-making entity uses law to protect its economic interests, undermining the students' informed participation in a process that could easily lead to their dismissal from the university.

Knowledge Structures

Organizational structures, whether within the university, the state and society, or the economy, are certainly significant to achieving justice in predictive student analytics. But this focus on organizational structures obscures knowledge structures involved in predictive student analytics.

These structures, found at intersections of policy, science, and technology, are equally important in protecting students from oppression and domination. The broader structural context of analytics algorithms is built on the assumption that predictive learning analytics is, in fact, predictive. This belief is upheld in many cases by scientism, the ideology that science is the only path to true knowledge and that scientific knowledge is inherently and unquestionably objective (Hyslop-Margison & Naseem, 2007; Peterson, 2003). In predictive analytics, scientism especially reflects an extreme version of traditional positivist science. Observation and law-like generalization are foundational to information science in spite of decades of challenges to this approach in the social sciences and education. It is, for example, common for analytics reports to quote naïve error rates rather than proportional reduction in error measures and to attribute causation even when using models that do not support causal interpretation (Baradwaj & Pal, 2011; Delavari, Phon-Amnuaisuk, & Beizadeh, 2008; Llorente & Morant, 2011; Parry, 2012; Thomas & Galambos, 2004; Vialardi, Bravo, Shafti, & Ortigosa, 2009) Model choice depends on assumptions about reality and intent, but these are rarely interrogated because of hyperpositivist beliefs about the efficacy of predictive analytics.

Scientism then hides other knowledge structures in which justice interests are found. An analytics process is part of a nexus in which problems, data and models, and interventions mutually support and inform each other. The underlying data is not an objective representation of reality but rather the end result of a translation process that is as much technical as it is social. These regimes of knowledge are structures laden with questions of justice, such as the recognition of particular racial or ethnic groups which in turn allows such groups to be represented in—or excluded from—decision-making by being included in or excluded from the data (Johnson, 2016a). These structures confer intellectual authority on developers while shutting down critical inquiry with flippant injunctions against arguing with facts and dismissive contrasts between sound data and unfounded instinct. This is not a consequence of bad data or bad models; these challenges are inherent in predictive analytics and are protected—along with those who use them to further their ends—by the structure of scientific knowledge claims itself.

This may be the most oppressive aspect of the "drown the bunnies" model: We believe our methods accurately tell us which bunnies to drown, for we have science. Those who suggest otherwise—for example, faculty members at Mount St. Mary's University who claimed that the data were inadequate to the intended use or students who can speak to considerations that are not quantifiable or even simply not collected because it didn't occur to anyone to do so—are denied the legitimacy of their claims by structures of knowledge that exclude information external to the process as non-knowledge. Students' self-development is hampered because data science says, with high confidence in precise quantitative scores and an acceptably low error (or, in Newman's words, "collateral damage") rate, that they are unsuccessful students. They believe that they are not in control of their lives. They lack the resilience to keep going after failure. They are introverted. They are depressed. Essentialized into who they were at the moment they took a survey—an assumption unsupportable at the most basic level in survey research (Zaller, 1992)—the problem-model-intervention nexus cuts off, seemingly without human action (though of course not in fact so, since a human wrote the algorithm and decision rules that the model applies), an avenue for self-development.

CONCLUSION

This structural analysis suggests that the "drown the bunnies" model fails because it is structurally unjust; it oppresses and dominates students. Students' self-determination is undermined by organizational forms that establish paternalistic—literally, *in loco parentis*—authority over them. Using this authority, students' self-development is subordinated to the needs of institutions, governments, and vendors. The well noted ethical concerns are most often a consequence of the organizational, political, and knowledge structures of student analytics: Privacy, individuality, autonomy, and discrimination are likely to be addressed most effectively where analytics processes aim at self-development and support self-determination.

Unfortunately, the analysis above suggests that the scope for individual practitioners to influence analytics in order to secure information justice is limited. While they can make some choices as best they can—particularly if there is sensitivity to structural concerns and a desire to support students' self-development and self-determination rather than just institutional performance funding formulae and key performance indicators—justice in predictive student analytics is a fundamentally structural challenge.

REFERENCES

Angwin, J., Mattu, S., & Larson, J. (2015, September 1). The Tiger Mom Tax: Asians Are Nearly Twice as Likely to Get a Higher Price from Princeton Review. Retrieved November 11, 2016, from https://www.propublica.org/article/asians-nearly-twice-as-likely-to-get-higher-price-from-princeton-review

Astin, A. W., Astin, H. S., & Lindholm, J. A. (2010). *Cultivating the spirit: how college can enhance students' inner lives*. San Francisco: Jossey-Bass.

Baradwaj, B. K., & Pal, S. (2011). Mining Educational Data to Analyze Students' Performance. *International Journal of Advanced Computer Science and Applications*, *2*(6), 63–69.

Boon, R. (2016, November). Sharing Data with Students to Inform Decision Making. Retrieved from https://www.airweb.org/eAIR/askeair/Pages/Rachel-Boon.aspx

Cegłowski, M. (2016). The Moral Economy of Tech. Presented at the 28th SASE Annual Meeting, Berkeley, California. Retrieved from http://idlewords.com/talks/sase_panel.htm

Christin, A., Rosenblat, A., & boyd, danah. (2015). Courts and Predictive Algorithm. Presented at the Data & Civil Rights: A New Era of Policing and Justice, Washington, D.C. Retrieved from http://www.datacivilrights.org/pubs/2015-1027/Courts_and_Predictive_Algorithms.pdf

Connor, K. M., & Davidson, J. R. T. (2003). Development of a new resilience scale: The Connor-Davidson Resilience Scale (CD-RISC). *Depression and Anxiety*, *18*(2), 76–82. https://doi.org/10.1002/da.10113

Davis, M. H. (1983). Measuring individual differences in empathy: Evidence for a multidimensional approach. *Journal of Personality and Social Psychology*, *44*(1), 113–126. https://doi.org/10.1037/0022-3514.44.1.113

Delavari, N., Phon-Amnuaisuk, S., & Beizadeh, M. R. (2008). Data mining application in higher learning institutions. *Informatics in Education*, *7*(1), 31–54.

Denley, T. (2013, September 4). Degree Compass: A Course Recommendation System. Retrieved February 21, 2017, from

Duckworth, A. L., & Quinn, P. D. (2009). Development and Validation of the Short Grit Scale (Grit–S). *Journal of Personality Assessment*, *91*(2), 166–174. https://doi.org/10.1080/00223890802634290

EAB Student Success Collaborative. (2015, January 21). The Murky Middle Project. Retrieved February 18, 2017, from https://www.eab.com/technology/student-success-collaborative/members/white-papers/the-murky-middle-project

Floridi, L. (2010). *Information: a very short introduction*. Oxford ; New York: Oxford University Press.

Foucault, M. (1995). *Discipline and Punish: The Birth of the Prison* (Second Vin). New York: Vintage Books.

Gilliard, C. (2016). From Redlining to Digital Redlining. Presented at the OLC Innovate, New Orleans, Louisiana.

Gosling, S. D., Rentfrow, P. J., & Swann, W. B. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, *37*(6), 504–528. https://doi.org/10.1016/S0092-6566(03)00046-1

Hoerger, M., Quirk, S. W., & Weed, N. C. (2011). Development and validation of the Delaying Gratification Inventory. *Psychological Assessment*, *23*(3), 725–738. https://doi.org/10.1037/a0023286

Institutional Effectiveness and Planning. (2015). *Postsecondary Institution Ratings System (PIRS) Evaluation*. Orem, Utah: Utah Valley University.

Jaschnik, S. (2016a, January 20). Are At-Risk Students Bunnies to Be Drowned? *Inside Higher Ed*. Retrieved from https://www.insidehighered.com/news/2016/01/20/furor-mount-st-marys-over-presidents-alleged-plan-cull-students

Jaschnik, S. (2016b, February 26). Tough Questions for Mount St. Mary's. Retrieved February 14, 2017, from https://www.insidehighered.com/news/2016/02/26/accreditor-demands-answers-mount-st-marys-numerous-standards

Johnson, J. A. (2014). The Ethics of Big Data in Higher Education. *International Review of Information Ethics*, *21*, 3–10.

Johnson, J. A. (2016a). Representing "Inforgs" in Data-Driven Decisions. In J. Daniels, K. Gregory, & T. McMillan Cottom (Eds.), *Digital Sociologies*. Bristol, United Kingdom: Policy Press.

Johnson, J. A. (2016b). The Value—and Limits—of Distributive Justice in Information Privacy. Presented at the Eastern Sociological Society 2016 Annual Meeting Digital Sociology Mini-Conference, Boston, Massachusetts.

Joseph, Y., & McPhate, M. (2016, February 29). Mount St. Mary's President Quits After Firings Seen as Retaliatory. *The New York Times*. Retrieved from https://www.nytimes.com/2016/03/02/us/simon-newman-resigns-as-president-of-mount-st-marys.html?_r=0

Kassim, H., & Menon, A. (2003). The principal-agent approach and the study of the European Union: promise unfulfilled? *Journal of European Public Policy*, *10*(1), 121–139. https://doi.org/10.1080/1350176032000046976

Larson, J., Angwin, J., & Parris Jr., T. (2016, October 19). Breaking the Black Box: How Machines Learn to Be Racist. Retrieved November 11, 2016, from https://www.propublica.org/article/breaking-the-black-box-how-machines-learn-to-be-racist?word=blacklivesmatter

Lee, P. Y. (2016, February 10). "Drown the bunnies": Mount St. Mary's president fires faculty for backlash against his "put a Glock to their heads" freshman retention plan. Retrieved February 14, 2017, from http://www.salon.com/2016/02/10/drown_the_bunnies_mount_st_marys_president_fires_faculty_for_backlash_against_his_put_a_glock_to_their_heads_freshman_retention_plan/

Llorente, R., & Morant, M. (2011). Data mining in higher education. In K. Funatsu (Ed.), *New Fundamental Technologies in Data Mining* (pp. 201–220). New York: InTech. Retrieved from http://www.intechopen.com/books/new-fundamental-technologies-in-data-mining/data-mining-in-higher-education

MDRC. (2016). Aid Like A Paycheck. Retrieved November 11, 2016, from http://www.mdrc.org/project/aid-paycheck

Mount St. Mary's University. (2016, August). Mount St. Mary's University Class of 2019 Survey. Retrieved from https://www.scribd.com/doc/299020003/Class-of-2019-survey

Nissenbaum, H. (2010). *Privacy in Context: Technology, Policy, and the Integrity of Social Life*. Staford, California: Stanford Law Books.

Parry, M. (2011). *Colleges Mine Data to Tailor Students' Experience*. Retrieved from https://chronicle.com/article/A-Moneyball-Approach-to/130062/

Parry, M. (2012). *College Degrees , Designed by the Numbers*. Retrieved from https://chronicle.com/article/College-Degrees-Designed-by/132945/

Perrotta, C., & Williamson, B. (2016). The social life of Learning Analytics: cluster analysis and the "performance" of algorithmic education. *Learning, Media and Technology*, 1–14. https://doi.org/10.1080/17439884.2016.1182927

Pratt, A. A. (2014, May 9). *University Retention and Resilience: Resilience and Hardiness in Undergraduate Students* (Undergraduate Thesis). Utah Valley University, Orem, Utah. Retrieved from http://contentdm.uvu.edu/cdm/ref/collection/UVUTheses/id/648

Radloff, L. S. (1977). The CES-D Scale: A Self-Report Depression Scale for Research in the General Population. *Applied Psychological Measurement*, *1*(3), 385–401. https://doi.org/10.1177/014662167700100306

Rawls, J. (2005). *A theory of justice* (Original ed). Cambridge, Mass: Belknap Press.

Ris, E. W. (2015). Grit: A Short History of a Useful Concept. *Journal of Educational Controversy*, *10*(1), 3.

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological Monographs: General and Applied*, *80*(1), 1–28. https://doi.org/10.1037/h0092976

Scherer, J. L., & Anson, M. L. (2014). *Community colleges and the access effect: why open admissions suppresses achievement*. New York: Palgrave Macmillan.

Schisler, R., & Golden, R. (2016, January 19). Mount President's Attempt to Improve Retention Rate Included Seeking Dismissal of 20-25 First-Year Students. *The Mountain Echo*. Mount St.

Mary's University, Emmitsburg, Maryland. Retrieved from http://msmecho.com/2016/01/19/mount-presidents-attempt-to-improve-retention-rate-included-seeking-dismissal-of-20-25-first-year-students/

Scholes, V. (2016). The ethics of using learning analytics to categorize students on risk. *Educational Technology Research and Development*, *64*(5), 939–955. https://doi.org/10.1007/s11423-016-9458-1

Scott, J. C. (1998). *Seeing like a state: how certain schemes to improve the human condition have failed*. New Haven: Yale University Press.

Singer, N. (2014, April 22). InBloom Student Data Repository to Close. *The New York Times*, p. B2. New York.

Solove, D. J. (2008). *Understanding privacy*. Cambridge, Mass: Harvard University Press.

Svrluga, S. (2016a, January 19). University president allegedly says struggling freshmen are bunnies that should be drowned. Retrieved from https://www.washingtonpost.com/news/grade-point/wp/2016/01/19/university-president-allegedly-says-struggling-freshmen-are-bunnies-that-should-be-drowned-that-a-glock-should-be-put-to-their-heads/

Svrluga, S. (2016b, February 12). The freshman survey that rang alarm bells for some at Mount St. Mary's. Retrieved from https://www.washingtonpost.com/news/grade-point/wp/2016/02/12/the-freshman-survey-that-rang-alarm-bells-for-some-at-mount-st-marys/?utm_term=.84f0075063f9

Thomas, E., & Galambos, N. (2004). What satisfies students? Mining student-opinion data with regression and decision tree analysis. *Research in Higher Education*, *45*(3), 251–269.

Two Crows Corporation. (2005). *Introduction to data mining and knowledge discovery* (Third). Potomac, MD: Two Crows Corporation. Retrieved from http://www.twocrows.com/intro-dm.pdf

Vialardi, C., Bravo, J., Shafti, L., & Ortigosa, A. (2009). Recommendation in higher education using data mining techniques. In T. Barnes, M. Desmarais, C. Romero, & S. Ventura (Eds.), *Educational Data Mining 2009: 2nd International Conference on Educational Data Mining, Proceedings* (pp. 190–199). Cordoba, Spain: International Working Group on Educational Data Mining. Retrieved from http://www.educationaldatamining.org/EDM2009/uploads/proceedings/vialardi.pdf

Young, I. M. (1990). *Justice and the politics of difference*. Princeton, N.J: Princeton University Press.

Zaller, J. (1992). *The nature and origins of mass opinion*. Cambridge [England] ; New York, NY, USA: Cambridge University Press.