Title

Advising the whole student: eAdvising analytics and the contextual suppression of advisor values

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Citation

This is a preprint. If you choose to cite this work, please use the following citation:

> Jones, K. M. L. (forthcoming). Advising the whole student: eAdvising analytics and the contextual suppression of advisor values. *Education and Information Technologies*. doi: 10.1007/s10639-018-9781-8

Acknowledgments

The author sincerely thanks the study's participants, who provided their time and openly shared their stories and experiences. Additionally, the author expresses his gratitude to Roderic Crooks and Rachel Applegate for critically reviewing early drafts of this article.

Conflict of Interest

The author declares that he has no conflict of interest.

This is the author's manuscript of the article published in final edited form as:

Jones, K. M. L. (2018). Advising the whole student: eAdvising analytics and the contextual suppression of advisor values. Education and Information Technologies. https://doi.org/10.1007/s10639-018-9781-8

Abstract

Institutions are applying methods and practices from data analytics under the umbrella term of "learning analytics" to inform instruction, library practices, and institutional research, among other things. This study reports findings from interviews with professional advisors at a public higher education institution. It reports their perspective on their institution's recent adoption of eAdvising technologies with prescriptive and predictive advising affordances. The findings detail why advisors rejected the tools due to usability concerns, moral discomfort, and a belief that using predictive measures violated a professional ethical principle to develop a comprehensive understanding of their advisees. The discussion of these findings contributes to an emerging branch of educational data mining and learning analytics research focused on social and ethical implications. Specifically, it highlights the consequential effects on higher education professional communities (or "micro contexts") due to the ascendancy of learning analytics and data-driven ideologies.

Keywords: Higher education, advising, learning analytics, educational data mining, professional values

1. Introduction

American higher education institutions are facing “intractable [financial] challenges” in the wake of the 2008 Great Recession and due to public disillusionment with the cost of earning a degree. The cost of undergraduate education has doubled over the last 30 years, and it continues to outstrip the rate of inflation and far exceed median income growth (Lorin 2014; Sydney et al. 2016). In years following the 2008 Great Recession, nearly all states imposed austerity measures on their public universities, which required institutions to raise tuition and fees to make up for lost subsidies (Oliff et al. 2013). Cuts reduced access to library resources, student services, and faculty, whose programs were shuttered due to financial instability and poor growth (Mitchell et al. 2016). A result of these financial cuts is that institutions have been tasked with doing more with fewer resources and students are pushed to perform at a higher rate with less support. Additionally, pressures by legislators continue to increase and, it is often the case that they want to measure their universities’ “performance and cost effectiveness” using verifiable and trackable data (Conner and Rabovsky 2011, p. 94).

To resolve these issues, many argue that turning to data analytics will bring about new paths of action and financial solvency (Campbell et al. 2007; Long and Siemens, 2011). Advocates of a data-driven approach to higher education look to Silicon Valley for inspiration. Target, Netflix, and Amazon’s collective use of big data to predict user needs and provide personalized services demonstrate ways in which universities may be able to “build a smarter university” (Lane and Finsel 2014, p. 6) that is more efficient and responsive to accountability measures. And with each online course producing thousands of data points, not to forget the thousands of other data points students create when they interact with other campus information systems, universities have a trove of data to drive their data analytics initiatives, which they define as learning analytics (LA) practices (Fonseca and Marcinkowski 2014).

Mining student data for analysis, much of which is identifiable, raises serious ethics questions. There are student privacy concerns associated with aggregating and analyzing data (Rubel and Jones 2017). And information ethicists argue that using data analytics, especially predictive measures, unfairly limits student autonomy and creates unjust systems in ways that run counter to normative expectations and widely accepted values in higher education (Johnson 2018; Rubel and Jones 2016). While these student-centered discussions are necessary, there are other significant questions regarding higher education professionals. Little research focuses on the compatibility of LA with the work practices and values of particular groups of higher education professionals (see Ferguson and Clow 2016; Ferguson and Clow 2017). It may be that professional groups have to bend systems and data to their needs (Dourish 2003), or they need to develop new literacies and skillsets to act on data and analytics insights (McCoy and Shih 2016). It may also be that LA is antithetical to professional norms altogether (Jones and Salo 2018).

Advisor perspectives have been absent in the literature. So, the driving goal of this research was to provide a platform for advisors to speak about their experiences and concerns related to eAdvising tools with informational and analytic affordances. This article reports findings from an interview-based study with professional advisors at a public higher education university in the United States, which addressed the following open-ended research questions:

1) What conditions specific to their institution prompt advisors, individually or as a group, to adopt LA systems, tools, or techniques?
2) Under what circumstances do advisors find LA to be morally problematic?

In summary, the findings cover the following themes. Advisors rejected the tools on some grounds, including usability concerns, moral discomfort, and a belief that using predictive measures violated a professional ethical principle to develop a comprehensive understanding of their advisees. Regardless of their views, administrators pressured advisors to adopt the tools. The discussion of these findings contributes to an emerging branch of educational data mining and LA research focused on social and ethical implications. Specifically, it highlights the consequential effects on higher education professional communities (or “micro contexts”) due to the ascendancy of LA and data-driven ideologies.

The article follows the ensuing roadmap. First, it begins with a literature review, focusing on the rising interest in big data-style methods and values in higher education. The section continues with background information on LA practices and goals before specifically addressing the application of LA in the advising context. The section ends with a discussion of the theoretical framing of the study. The article continues with information on the study’s design, including the sampling methods, collection procedures, data analysis strategies, and the evaluative measures I employed. The findings follow, which highlight the grounded, thematic categories developed from analyzing the data. I conclude the article with a theoretical discussion of the consequences of what I call “contextual suppression,” which include the coding out of advisor values, deprofessionalization effects, and the contradictions embedded in the “personalized education” argument as it relates to advising.

2. Literature Review

2.1. The Data Turn in Higher Education

For decades, information technology systems on university campuses have worked to support and advance institutional communication, collaboration, and record keeping, among other things. That institutions can and should mine data within these interconnected systems, however, is a relatively recent phenomenon (Lane and Finsel 2014). In part, this is due to advancements in and lower financial barriers to data-related technologies (Goff and Shaffer 2014). But it is also due to the fact that campus information systems are creating a “data explosion," effectively developing more volume and variety of data at greater speeds (Long and Siemens 2011, p. 32). Many within and outside of higher education now claim that "Big Data" has arrived on campuses and in classrooms (Parry 2012).

Institutions are building advanced data warehouse systems and techniques to capture, organize, and create wider access to that data to capitalize on the potential of data analytics (Cheslock et al. 2014). Greater access to so-called "digital breadcrumb" behavioral data and personal information opens up opportunities for analytic practices in higher education, much like businesses have used to profile users or consumers (see Mayer-Schönberger and Cukier 2014). Data analytics use statistical methods to "uncover relationships and patterns within large volumes of data that can be used to predict behavior and events" (Eckersen 2007, p. 5 as cited in van Barneveld et al. 2012). Studying learning behaviors in data and, subsequently, improving learning environments and resources may improve institutional operations by making more informed uses of resources in ways that bring about greater efficiencies and effectiveness (Goldstein and Katz 2005; Long and Siemens 2011).[1] The surge of interest in higher education data mining is situated under the umbrella term "learning analytics."

2.2. Learning Analytics

Learning analytics (LA) is the implementation of data mining and analytic methods for the purposes of investigating and understanding learning behaviors to optimize learning

[1] It may also be the case that while student learning improves, the cost to deploy LA tools and strategies does not reap financial savings. In this case, LA may not be justifiable given stakeholder pressures to reduce the cost of earning a higher education degree. To recoup the lost savings, it is plausible that institutions may resort to selling data or data products, or negotiate for a lesser amount for vendor products and services in exchange for data; there is some evidence of this already (see Unizin 2018). For more on this argument, see Rubel and Jones (2017) or Jones and Salo (2018).

environments, learning processes, and institutions of learning (Siemens 2012; van Barneveld et al. 2012). With LA, student behaviors once “unseen, unnoticed, and therefore unactionable” are becoming known by enabling institutional actors and researchers to interrogate relationships and patterns related to learning (Bienkowski et al. 2012, p. ix). With the array of information systems on which students rely making their behaviors, interactions, and preferences transparent, some administrators see every student as an analyzable data point and “test subject” (Bienkowski et al. 2012, p. ix; Brown 2017).

Higher education institutions have deployed LA technologies and methods to achieve disparate goals. Admissions departments are analyzing application information in addition to data left on institutional social media accounts and via e-mail response rates to predict student enrollment (Felton 2015; Goff and Shafer 2014; Hoover 2015). When students arrive on campus, some institutions are tracking ingress and egress from buildings to understand campus engagement, monitor attendance, and predict retention rates (Belkin 2015; Ferguson et al. 2016; Parry 2012). Mining geolocation data derived from radio frequency identification (RFID) signal activity from student identification cards, student connections to campus wireless network hotspots, and student identification card swipes also informs these types of analytics (Cook 2016; Hall, 2016). Learning management systems, such as Blackboard, Desire2Learn, and Canvas, incorporate tracking tools to inform instructors of student access to course materials and student engagement. And these tracking strategies support predictive algorithms that alert instructors as to whether or not a student is likely to succeed in their courses based on historical data and current performance (Arnold & Pistilli 2012). Academic libraries are beginning to participate in LA practices as well by correlating library use with class performance, using the resultant analytics to inform instructional interventions (Jantti 2016). Of primary interest in this study, however, is how higher education is using LA for advising purposes.

2.3. Advising Analytics

Learning analytics (LA) advocates argue that advising work could be improved and the capacity thereof increased by analyzing the growing troves of student data and employing analytics. Actively monitoring student behaviors and learning progress expressed in data, they argue, enables advisors to diagnose problems more quickly to develop just-in-time interventions and match resources based on students' needs more effectively (Aguilar et al. 2014; Kraft-Terry and Kau 2016). For instance, they could match students to a plan of study aligned with their skills and interests, as well as better provide financial, social, and, increasingly, mental support and services. Real-time diagnostic analytics are helpful, but they only address past, present, and near-term problems; they fail to predict problems that may occur in the future.

To forecast future issues in a student's academic life, advisors are increasingly examining student success predictions. There are some notable cases of predictive advising analytics; for instance, consider the case of Georgia State University (GSU). GSU's "use of predictive analytics and proactive advising interventions" increased the capacity and reach of its advising office, which had a ratio of 700 students for every one advisor (Renick 2014; University Innovation Alliance n.d., p. 1). According to the *Chronicle of Higher Education*'s reporting, "GSU analyzed 2.5 million grades earned by students in courses over 10 years to create a list of factors that hurt chances for graduation" (Kamenetz 2016, para. 7). With the help of a consulting firm, GSU built an early alert system, which provided over 800 different types of tailored alerts "aimed at helping advisors keep students on track to graduation" (Ekowo and Palmar 2016, p. 3). The advising analytics project enabled GSU to "increase semester-to-semester retention rates by 5 percent and reduce time-to-degree for graduating students by almost half a semester," effectively saving “Georgia taxpayers…approximately $5 million” by more quickly graduating students (University Innovation Alliance n.d., p. 1).

Other institutions have deployed advising systems to evaluate how a student’s choice of major and achievement in courses compare with peers who have been successful on the same path (Young 2011). At Austin Peay State University, for instance, algorithms recommend courses to students, prioritizing courses students need for graduation, courses core to the university’s curriculum, and courses in which the student is expected to be academically successful (Denley 2013). Arizona State University’s (ASU) eAdvisor system helps students choose among the institution’s 290 majors to map out their path to graduation (Kamenetz 2014). If the student fails to sign-up for a course on time or does poorly in a course for which she’s enrolled, the system “cracks a whip” and marks them off-track; too many red flags from the system triggers automatic meetings with professional advisors, potentially resulting in a situation where students are forced to change their major (Parry 2012, para. 16). Like GSU, ASU’s evaluation of the eAdvisor system and its outcomes showed some significant findings. 33% of students once in exploratory majors dropped to 8%, and the system created $13.8 million in cost recoveries in the areas of advising and instruction; additionally, the four-year graduation rate increased by 9% relative to eAdvisor’s introduction (Burns et al. 2015).

2.4. A Micro-Contextual Research Focus

The information flows supporting learning analytics (LA), and the actions resulting from data analysis, have raised significant questions. For instance, the ethics of predicting student behaviors and subsequently intervening in student life surfaces frictions regarding power discrepancies, information asymmetry due to black-boxed algorithms and systems, and Gordian privacy problems concerning autonomy and consent (Pardo and Siemens 2014; Rubel and Jones 2016; Rubel and Jones 2017). Scholars and practitioners continue to debate the issues and approaches to these student-centric concerns. Other researchers are examining questions about the structural effects of educational data mining (Zeide 2017) and the political pressures to adopt LA (Selwyn 2017). These examinations of macro-level concerns are important, but what is lacking in the literature is a focus on specific, micro-contextual groups of higher education actors, their uses of LA, and an examination of particularized problems.

The amalgamation of values, norms, ethics, and technologically-mediated practices takes on different concerns when we consider how LA affects micro-contexts populated by professional groups (e.g., advisors, instructors, librarians, educational technologists) within the larger context of higher education. Defined, "[c]ontexts are structured social settings characterized by canonical activities, roles, relationships, power structures, norms (or rules), and internal values (goals, ends, purposes)" (Nissenbaum 2010, p. 132). Actors within contexts conduct practices in order to achieve specific ends (e.g., work towards a goal, motivate other actors to adhere to a context's mission, etc.). These efforts, and the ends to which they are put, are regulated by "behavior-guiding norms," which the context establishes to, in part, arrange its practices, and drive its teleological—or value-driven—orientation. Micro-contexts are often "nested" within larger contexts. For example, a public elementary school co-exists with its middle and secondary counterparts within a larger school district. Nissenbaum (2010, p. 137) writes that micro-contexts may overlap, conflict, and compete with one another in ways where "norms from one context prescribe actions that are proscribed by the norms of" another context. This conceptual framework enables needed scholarship into normative compatibilities and frictions among higher education's micro-contexts. Work by Jones and Salo (2018) and Jones and LeClere (2018) highlights how micro-contextual research can illuminate micro-contextual discord. Their collective work analyzes academic librarianship and highlights particular uses of

LA tools and strategies. The research foregrounds professional librarian ethics commitments with regard to, inter alia, privacy and intellectual freedom to assess and critique the disconnect between administrative and librarian interests. While this work is valuable, the approach limits the practicability of its recommendations; it is primarily written at a conceptual level using information ethics theories to support its claims. Empirical work that gives voice to micro-contextual actors can "[dive] into the socio-technical sphere" and lead to greater analytical depth (Macfadyen and Dawson 2012, p. 161). The study described herein focuses on academic advisors and their interactions with and perceptions of eAdvising analytics, which follows a micro-contextual approach and begins to fill a gap in the literature.

3. Study Design

3.1. Data Sampling and Collection Procedures

For this study, I conducted 14 face-to-face interviews at a single case site over four months. I used criterion and nominated sampling techniques to request subject participation (Creswell 2013). Participants in this study self-identified as professional advisors who worked with pre-program undergraduates and were affiliated with my case site. Participants had a range of experience; some had been in the advising profession for less than two years, while others had been advisors for their entire professional career with over ten years of experience. The advisors advised undergraduates who were working towards admission into a selective program of study requiring a specific set of prerequisite courses and a certain grade point average. Each advisor was reportedly responsible for around 300 advisees. I initially identified subjects based on publicly available information listed on the case site's website.

Interviews followed an IRB-approved interview protocol with exempt status. The protocol covered three different areas: descriptions of participants' role as advisors; questions about their professional values, goals, and interests they serve; and inquiries about their use of eAdvising technologies. Questions within these areas were open ended and allowed participants to reflect on their professional experiences and perspectives. As I analyzed data and built categories, which I describe in the following section, I asked more specific questions that attended to the category's attributes. After finishing an interview, I asked the participants to nominate other participants who fit my criteria. Most interviews lasted about an hour. I had no prior relationship with the participants before I started the project. When I felt it necessary to fill in contextual information not available from the participants, I researched publicly available documents about the participants' institution, the administration of the institution by its state's government, and the advising tools.

The case site was a public university in an urban city with a Carnegie Classification undergraduate profile described as "four-year, medium full-time, selective, higher transfer-in" with high research activity. The institution's four-year graduation rate stood about 25% for all undergraduates, with students of color around 20% and white students at about 30%. Over 30% of the institution's undergraduates received Pell Grants; this is a notable decrease from years past, and it reflects recent cuts to the Pell Grant system. Student retention and graduation rates directly affected an individual school's financial standing, along with the university's, due to the institutional application of a Responsibility Center Management (RCM) model for budgeting, which was used to motivate revenue generation and careful stewardship of resources at the school level.

I chose this case site in part because it provided opportunities for unique data given its advising structure, student makeup, and political background. First, I presumed correctly that advising pre-program undergraduates put advisors in the position of tracking student progress closely and providing dual-plan options. Second, the institution has a diverse student body and struggles with its retention and graduation statistics, which as the literature details is an important justification for adopting learning analytics technologies in the advising context. Third, the institution's budget from the state is in part dependent on the level of success it achieves related to, inter alia, degree attainment, on-time graduation rate, and student persistence. This performance funding scheme has been active for over ten years, but it is tweaked from year to year to measure outputs closely related to student success and the degree to which student outcomes support the state's economic needs. All these things combined led to interesting intersections between emergent data.

3.2. The Research Paradigm

I situated this study in the naturalistic research paradigm because it was congruent with the methods I employed. Briefly, naturalism aims to bring to the fore idiographic processes, practices, facts, and values embedded in sites of action and discourse (Lincoln and Guba, 1985). Interpretive research situated in the naturalistic paradigm is especially fruitful when research questions consider socio-technical issues, processes, and information technology development and use, or non-use as may be the case (Darke et al. 1998; Walsham 1993; Wyatt 2003). Human sensemaking is in part shaped by the array of technological artifacts, tools, and systems with which one can interact (Klein and Myers 1999). Consequently, individuals make particular choices about how to deploy those tools based on, inter alia, their values, goals, and needs; but, those choices are also shaped by larger social (e.g., norms, rules, and resources) and technological (e.g., design limitations and freedoms) structures (see DeSanctis and Poole 1994; Orlikowski 1992). Interpretative work in this area enables a researcher to investigate and expound on the interplay between technological design and social action and values, which was the intent of this project.

3.3. Grounded Theory Methods and Evaluative Measures

I followed constructivist grounded theory methodology and employed its related methods for this interpretive case study because of its alignment with naturalistic inquiry and "lies squarely in the interpretive tradition" (Charmaz 2006, p. 130). As a methodology, it emphasizes the interpretative nature of qualitative research; as a kit of methods, it focuses on eliciting how participants view reality, construct their worldview, and express agency. Grounded theory methods include coding, theoretical sampling, and memoing as ways to develop credible themes and useful findings. I employed these three techniques in order to iteratively build a storyline and home in on particular insights that highlighted telling socio-technical interactions. The coding process went as follows. First, I reviewed each digitally recorded interview. While listening to the audio, I took detailed notes. I reviewed those notes in comparison with notes I took while participating in the interview. After compiling the notes, I built visual code categories using the MindNode mind mapping application. Each subsequent interview followed this process, which led to iteration, record keeping of key quotes, and, in part, theoretical saturation of emergent categories. Ultimately, I achieved theoretical saturation with targeted questioning during interviews to test the stability and characteristics of a given category of related codes (Holton, 2007). Only after seeing repetitive, confirmative data in my categories did I stop interviewing; thus, I have high confidence I reached theoretical saturation.

I pursued three criteria to assess the rigor of my grounded theory-based study: originality, dependability, and credibility (Charmaz 2014). This work is one of the first to consider on-the-ground issues related to advising and learning analytics technologies, which in part demonstrates originality. This article has gone through "quality management checks," or reviews and critiques, by trustworthy scholars familiar with my methods and research background, which adds to its dependability (Flick 2007, p. 135). I aimed with my literature review to show an "intimate familiarity" with the issues and context to enhance credibility (Charmaz 2014, p. 337). These things combined work to raise confidence in the six thematically intertwined findings that follow.

4. Findings

4.1. Knowing the Whole Student

The unique makeup of their advisees and their particular needs shaped how advisors approached the advising process and crafted their professional values. Recall that the student population for the case site was diverse and, based on the percentage of students receiving Pell grants, not financially well off. Many advisees, many participants remarked, were attempting a full load of courses (12 or more credits) while working near, at, or above 40 hours per week. Moreover, some advisors also described how their pre-program advisees have unique needs, interests, and problems separate from students who have already entered into the program of study. Students at this stage of their academic career are contemplating the deeply personal process of choosing a program of study; additionally, they are trying to navigate the institution and work out new responsibilities in their personal lives: financial, social, and otherwise. Should students fail at this balancing act, they encounter the stark truth that they have not accomplished the level of academic success necessary to meet the competitive program's high admissions standards for which they applied for admission. All these characteristics about student life shaped how advisors aimed to assist their advisees.

Nearly all participants expressed that knowing their advisee, the "whole student," was necessary in order to determine how best to tailor interventions and provide advisees support. This was not a simple process, and it often took significant effort to develop a trusting relationship between the advisor and advisee. Advisors emphasized that establishing interpersonal trust enabled them to work towards a place where students were willing to disclose their struggles and aspirations. And getting to a point where students opened up personally to advisors helped both parties to discuss how academic success was intertwined with and in part determined by the student's ability to manage personal issues.

Knowing students on a personal level was more than just an advising strategy; it also represented their professional ethos. Many participants relayed during interviews how they valued having "compassionate conversations" that enabled them to work as a partner with students through struggles and towards successes. And working closely with their advisees, they believed, helped break down stigmas around failure and struggling in a safe, supportive environment. Advisors were driven to "hold students accountable" for their actions and "have the hard conversations," but to do so in a way that conveyed to students that they cared. They valued seeing their students recognize their weaknesses and helping them find a path forward.

What also motivated their work was talking with students about what success looks like and the many different pathways towards success. Too often, some advisors said, external forces (e.g., parents, society) drive students to choose a career pathway before they are ready. These pressures "paralyzed" students, causing them anxiety in ways that stopped them from thinking about their interests and goals. Many advisors saw themselves as "coaches" who can develop in their students skills related to introspection and goal setting. A major motivating factor for this particular strategy, some advisors said, was getting their advisees to see the larger value in their academic experience and degree beyond just a stepping stone to a career and financial stability.

4.2. Designing Advising into Technology

A majority of advisors recognized that the academic choice sets and resources they provided students—and the outcomes those choices worked towards—were framed in part by pressures from the wider institution and the institution's legislative stakeholders, which led to the development and adoption of new advising technologies. Participants notes two specific actions by the state government.

First, their institution's home state required each of its publicly-funded institutions to develop degree maps according to degree-granting programs in ways that charted how students should progress towards their degree. The state argued on its website that this initiative would encourage students to commit to a college major as soon as possible and reduce enrolling in unnecessary credits. This initiative spurred the creation of a homegrown degree map system, which I have assigned the pseudonym "Degree Tracker."

The second initiative concerned the state's committee on higher education passing a resolution that encouraged so-called "banded tuition" at its state-funded institutions of higher education, which my case site institution adopted for the 2016-2017 academic year. Banded tuition incentivizes students to commit to 15 credits per fall and spring semester by guaranteeing the same rate of tuition for students taking between 12 and 18 credits. The state argued that banded tuition increases student success, moves students towards graduation quicker, decreases student debt, reduces post-graduation wage losses, and increases the competitiveness of state-funded institutions in the higher education marketplace. To work towards these goals, the advisors began using Student Success Forecast, or "Forecast" for short.[2] I detail both Degree Tracker and Forecast below.

Degree Tracker was designed and built with the intent of "smoothing" the path to timely degree completion, but it was primarily developed, as one advisor said, "because the law says so." The system was put to the task of addressing a number of issues. First, Degree Tracker was designed to help students select degree programs for which they are a good academic fit. Second,

[2] "Student Success Forecast" is a pseudonym.

it steers students to enroll in courses that count towards their major's requirements. Third, it seeks to provide more timely and accurate information to advisors regarding the ever-changing landscape of the institution's curriculum. Finally, it works to streamline course transfer processes when students arrive from other campuses.

Documentation in support of the Degree Tracker initiative characterized students as overwhelmed, under-informed, and unable to make complex decisions regarding course scheduling and degree planning. The institution, the documentation argued, puts students at risk and potentially wastes valuable resources when it fails to provide degree paths. The documentation references research by Richard Thaler and Cass Sunstein, whose jointly developed theory of libertarian paternalism argues that positive choice-making is improved when individuals are provided pre-determined choice sets (see Thaler and Sunstein 2003; Sunstein and Thaler 2003). Based on this theory, the documentation argues that Degree tracker can nudge students in the right direction and reduce resource expenditures by students and advisors alike; and while doing so, the system can reduce the amount of work advisors incur. Degree Tracker, the documentation states, provides useful information to students regarding degree pathways, who often self-advise instead of communicating with their assigned advisor.

The second advising technology my participants used was Forecast, which had three affordances that uniquely informed advising. First, Forecast was designed with the ability to create highly specific lists from the entire student body based on data and information housed in the institution's student information system, including academic, demographic, and limited financial data from a student's profile. Using this information, advisors developed targeted campaigns to reach out to specific types of students, deploy customized interventions according to group profiles, or to match sets of similar students to academic opportunities and degree pathways.

Second, Forecast provided advisors predictive measures about students. One measure informed advisors of their advisees' likelihood to graduate from major programs provided by the institution. The student's academic history and how that history compared to similar students informed the predictions. Another measure informed advisors of potentially difficult courses associated with particular plans of study. Finally, a risk score was associated with each advisee, indicating whether or not students were at a low, moderate, or high risk of failing to graduate in their chosen academic program. According to documentation about Forecast, this statistical model included factors related to credits taken per semester, rate of progress towards one's degree, performance in courses compared with one's peers, focused coursework and course load in a particular program, success in courses at prior institutions, and performance in high school and with regard to standardized tests. Documentation about Forecast disclosed that the system used real-time, in-semester data to inform its proprietary models and predictive scores.

Third, the system compared each advisee to historical data representative of peers who had been successful in her chosen program. For instance, a student in pre-law would be compared against other pre-law students in multiple, subject-based areas such as "humanities" or "business, economics, and mathematics." The indexed score of successful pre-law students in an area would then be compared to the advisee's score, in effect showing advisors how their advisees' performance aligns with that of successful peers in the program. A large discrepancy in scores increases the student's overall risk score due to the lack of alignment between the student's performance and her peers who succeeded in the past.

4.3. Rejecting Advising Technologies

Administrators introduced the Degree Tracker and Forecast systems to advisors as tools that would enhance their work and, to an extent, support the main aims of learning analytics technologies (e.g., reduce the time to earn a degree, increase retention rates, etc.). While some advisors noted that the intentions driving the adoption of these tools were good and justifiable, these things mattered little when put to the task of day-to-day advising. Nearly all advisors argued that both of these systems had a variety of flaws which made them, to varying levels, incongruent with their needs.

Consider the lukewarm response a few advisors gave when asked about Degree Tracker. Participants noted that it often failed to accomplish the goals that motivated its development and implementation. Broadly speaking, instead of improving the course and degree selection process and aiding the advising experience, it created even greater complexity and added to the advising workload. From a usability perspective, several advisors commented on the fact that the whole process of interacting with the system was difficult to grasp for students and themselves, which only complicated advising sessions. More specifically, the system presented degree paths in static form, making it impossible for advisors and students alike to manipulate the path to respect student interests and needs. Degree Tracker was also viewed in a negative light because advisors saw it as another tool in an already crowded advising toolbox. In fact, a few advisors characterized the addition of Degree Tracker in a harsh light, stating that administrators “foisted” it on them without considering how its affordances overlapped with extant technologies and proven advising worksheets.

Many participants had similar remarks about Forecast, especially where the predictive analytics were concerned. Across all advisors, not a single one used the predictive scores in any strategic way. It was easier and more effective to investigate a student’s transcript, hold a conversation with the advisee, and use their professional experience and honed intuition to make judgments about students and develop personalized strategies. When asked why the institution had and continued to invest in this technology even though advisors did not use it as intended, they stated that the institution was trying to “keep up with the Joneses” and stay abreast of trends in educational technology. One advisor argued Forecast signaled an adoption of “big data empiricism,” explaining that “data science feels science-y” in ways that lend it more credibility than an advisor’s professional insight.

The rejection of Forecast was also due to a lack of trust in the data and models that informed the predictive scores. Some participants reported that it was unclear when the systems were updated with the most recent version of data from the central student data warehouse, and the data they did see was not always accurate; sometimes information they knew should be accessible was not. As one advisor put it, “analytics are only as good as what they are programmed to do, and what data they [analyze].” Similarly, another advisor stated that “with data, you can manipulate it any way you want.” Another advisor stated that he found himself “interpreting the interpretations” of the predictive measurements because he was unsure of the sources of the data and whether or not the statistical techniques were valid.

While there was no initial requirement to use Forecast in any particular way, low usage among advisors of the system resulted in social pressures by advising administrators. In the first year of the tool’s deployment, some advisors reported that low usage was logged and reported to the administrator, who subsequently “took [advisors] to task” for not using it in their advising practices. When I asked if logging their tool usage was standard, they said no. However, they imagined how tracking would increase and usage penalties would become more severe if the state legislature ratcheted up pressures with respect to student performance metrics. The same participants noted how their workplace performance could plausibly be judged based on system logs that monitored their communications with advisees, usage of analytics in interventions, and how those interventions influenced their advisees' speed of progress towards a degree.

4.4. Conflicts with Advisor Values

Degree Tracker forced many advisors to change the way they held conversations with their students by adopting a "prescriptive advising" strategy instead of one that responds to advisee needs and allows for open, transparent conversations; advisors characterized this as an affront to their professional values. Planning this way, one advisor expressed, runs counter to traditional methods of advising and is not well thought of by professional advisors. Degree Tracker effectively forced advisors to start advising conversations with the institutional plan of study instead of working through an interpretive conversation. In conversations, students express their interests and advisors use their professional opinion and skills to match students to courses and programs.

Degree Tracker's rigid paths did not reflect a student's individual needs. The paths of study worked as "templates in a perfect world," as one advisor said, and her peers commented that they had rarely seen students successfully follow a pre-designed program path. "In my experience," said a participant, "it's amazing how few students can actually follow a four-year plan to the letter of the law." This is due in part to how students have different definitions of what success looks like and how to get there, and the misalignment between a student's personal needs and the way Degree Tracker prescribes "right" paths to a degree.

When students' course paths were out of alignment with what Degree Tracker indicated, advisors pointed out that this caused notable stress among advisees. They argued that students have different paths to work towards their degree, and the Degree Tracker system's prescribed pathways could not account for students who needed remedial courses; and according to a few advisors, students perceived that the system was punishing them for taking exploratory courses off of the set pathway to the degree. To one advisor, Degree Tracker was saying to students not on “the right pathway” that “you don’t fit our system,” that the students were “bringing [the institution] down.” These signals worked against advisors, who were trying to help students define their goals and individual pathways to success.

Advisors recognized that not using Degree Tracker as intended and rejecting Forecast’s predictive tools ran counter to institutional goals, especially related to time-to-degree and retention metrics. All participants indicated that their first responsibility was to serve their advisees’ interests before their institution’s. About this, an advisor stated, “we aren’t here just to promote the school[’s interests] and keep [students] here no matter what.” Participants argued that they had a professional responsibility to serve their advisees’ interests by putting all options on the proverbial table to help students make fully informed choices with respect to their academic and professional paths. Even though the institution might prefer students take courses within the 12-to-15 band of credits, for instance, they argued that suggesting to advisees that they take fewer credits in a semester or taking courses that do not count towards one’s degree would be the student-centric approach to advising if the situation warranted such advice.

4.5. Protecting Against Self-Fulfilling Prophecies

A majority of participants passionately argued that the preset degree paths in Degree Tracker and the predictive measures in Forecast held the potential to create harmful self-fulfilling prophecies. They felt that these affordances in the advising systems signaled to advisors and students alike a predetermined path and set of possibilities. Specifically, they presented a *singular* course of action that would lead students to academic success, which both parties in the advisor-advisee relationship could internalize with different negative effects.

For other advisors, degree pathways and predictive analytics could potentially bias their view of their advisees. One advisor put it succinctly, “I don’t want to have a predetermined notion about a student I’ve never met.” By focusing advisors’ attention on how a student should get to graduation or what area of study a student is predicted to do well in, advisors were concerned that their perception of a student’s potential would be swayed by the metrics presented in the technologies. As another advisor said, “If there’s a .01 percent chance a student can be successful at something, he can be successful.” Whatever the analytics predicted, the advisors did not want to shut down academic paths prematurely.

For students, Degree Tracker did not make students aware when they were “off track” in any particular way, which limited the harm from self-fulfilling prophecies; students had no access to the predictive measures in Forecast. When I asked if students should be able to see their Forecast scores, advisors answered with a resounding “no.” These participants were acutely aware of the possibility that some students simply did not have the mental or emotional capacity to understand and critically analyze the degree paths and predictive measures, especially when students were off track or at risk. For instance, an advisor posited that some of his advisees would characterize “a red flag as an ‘F’ grade,” even though that is not the purpose of flags nor what they represent. “It could be frightening to students to see those analytics,” said one advisor. And, added another participant, some students may “make up their own stories about why they are in the red,” or predicted to do poorly in a class or program of study. Similarly, a green flag could be misinterpreted as a “stay-the-course flag,” even though improvements could still be made. They characterized this concern as a human development issue, arguing that “students are very sensitive to being judged.” Most advisors were adamant that student access to Forecast’s predictive measures should be allowable only with an advisor by their side interpreting and contextualizing the scores; they argued this approach could mitigate the potential for harm by self-fulfilling prophecies.

4.6. Treating Students Like a Number

Analytics that showed which students were predicted to be at risk of semester-to-semester retention especially raised an ethical question around treating students fairly. The potential existed for advisors to ignore high-risk students who would, for instance, need more resources, advisor time, or whose situation was simply too burdensome to address. It would simply be easier to focus attention on students who had a better chance at succeeding with an advisor's guidance and attention. About this concern, an advisor argued that she had an "obligation to help all students as much as possible under all circumstances." Advisors argued that this concern further supported their case that the analytics should be bypassed and replaced with close, interpersonal relationships with their advisees in order to treat all advisees fairly.

Building on their concerns about fairness, some participants stated that prediction-based advising put too much emphasis on data mined for the advising systems without giving students a chance to speak for themselves. About this, an advisor stated, analytics "dehumanized" students by treating them "like a number." "Success is different for each student," argued another advisor, and advising based on statistics runs counter to their professional position that all students have unique issues, capabilities, and goals that need to be accounted for and respected in the advising process.

5. Discussion

5.1. Contextual Suppression

Institutions are putting significant effort and expenditures into developing the social and technical infrastructures required to maximize insights from learning analytics (LA). But, in the course of pursuing the goals proponents of LA seek to accomplish, harmful effects are accruing as these technologies are introduced into institutional actors' workspaces and workflows. Some of these issues may simply require, among other things, retraining in order to make better use of data analytics, but larger conflicts may be intractable; my findings reveal that the latter may be the case where academic advisors are concerned.

The data revealed that the analytic and other informational strategies designed into both the Forecast and Degree Tracker systems—systems required in part by legislative action and supported by institutional administrators—are not respecting advisors' values. The situation is not one of simple disagreement, nor is it *just* a matter of advisors choosing not to use the technologies because of their poor usability and usefulness (although, this was part of the reason). What is at play here is a contextual conflict. That contexts conflict is not uncommon or unexpected, but what is notable in this case is that the values in the advising context are at risk of subordination by administrators who support LA. I call this "contextual suppression," a concept that compliments Michael Walzer's argument that "tyranny [occurs] when goods of one sphere intrude into, or become dominant in, not only one sphere but many" (Nissenbaum 2004, p. 145). Friction between two or more contexts whose values and interests are misaligned, if not directly opposed to one another in some cases, creates a situation where actors in one or more micro-contexts try to impose their values, norms, and goals on another micro context. The following sections layout thematic implications of contextual suppression as it relates to advising.

5.2. Encoding Student Success

The disharmony between administrative and advisor contexts was arguably less noticeable in years past when both sets of actors used different strategies, including technologies, to work towards a shared goal—student success (however defined). But as data mining in higher education has become more centralized and systematic, and the pressure to use analytics more pronounced, administrators are leaning on advisors to take up analytic strategies that the latter finds questionable, at the least, and morally suspect, at the most. These tools are hardcoding in so-called “productivity” and “institution-centered” definitions of student success, which run counter to the student-centered definitions participants expressed (Wallace and Wallace 2016).

While advisors do agree that student learning, retention, and graduation are *good* ends, and they are aware that this perspective is a part of their professional principles (see NACADA 2005), they do not agree with administrators who argue that these are the *only* metrics by which to define student success. The participants in this study expressed student success as something akin to Love’s (2008, as cited in Wallace and Wallace 2016) definition, where students are architects of their paths towards success, or according to Harrell and Holcroft’s (2012, para. 8) view, which is that “the truest definition of student success is determined by the goals and personal situation of each individual student.” Their view, however, is not respected in system design. Instead, administrative values motivated and became “exogenously inscribed” (Friedman and Kahn 1997, p. 1179) in the design of the eAdvising tools, including the data, the predictive models, and the interfaces.

5.3. The Advising Machine

Emerging advising technologies repress the advising context by decreasing the need for expert labor by replacing honed professional experience and advanced educational training with analytic tools and degree pathway applications. These emerging technologies deemphasize professional knowledge by enabling students to use advising tools on their own. In this study, the digital provision of advising was situated to augment student-advisor interactions, thus limiting the student’s ability to self-advise; in fact, advisors actively worked against allowing students to self-advise with the tools discussed herein. So, deprofessionalization effects were limited. However, resituating these tools to enable student self-service would bring about the harmful consequences of eroding the student-advisor relationship and limiting the control advisors have over their labor (Apple and Jungck 1990). Instead of human advising, students would work with advising machines driven by algorithms and analytics.

It is important to question why institutions are expending resources on these technologies, especially given longstanding investments in professional advisors. Selwyn (2014, p. 62) argues that educational institutions are taking up data-driven educational technologies and building up the requisite infrastructures to reduce “educational processes and relationships to forms that are easily quantifiable,” all towards supporting new managerial strategies that increase administrator control to the detriment of individual autonomy among educational professionals, like faculty and advisors. As I highlighted in the findings, the advisors’ manager began tracking their use of Forecast, and scolded them for low usage; some advisors responded by logging in and clicking around, all to present a façade of use, relieve themselves of managerial pressures, and decrease the possibility of punitive action. At another institution under different circumstances, it is plausible to think that advisors will be disciplined into using advising analytics, regardless of their professional concerns. Doing so will align advisor labor with managerial needs in support of the dominant “computational” ideology, which argues that just the right mixture of data, algorithms, and technological systems can solve the seemingly intractable problems facing higher education (see Golumbia 2009; Lanier 2010; Selwyn 2014).

5.4. The (De)Personalization Paradox

Learning analytics, such as those within the Forecast system, are often characterized by educational technologists and pundits as one of the main pathways towards truly personalized education. By building up large data stores inclusive of student information and behaviors, analytics can profile students, match them to just-in-time resources, and predict areas in which they may or may not be successful. Educational technology critics think otherwise. We can understand “personalized” education as being less about the needs of the learners and more about serving the interests of higher education institutions—namely improving profits and their position with accountability hawks—by surfacing analyzable data for the purposes of demonstrating politically prudent outcomes; in fact, any talk of “personalization” by institutional administrators may simply be rhetorical “window dressing” (Selwyn 2017, p. 160). Institutional administrators and those to whom they report (e.g., the state legislature), perceive students as objects of measurement, whose output metrics (e.g., retention, graduation, employment, salary earnings) can be improved with technology-enhanced programs supported by systems of dataveillance.

As was the case with Forecast, algorithmic analysis of student life did not aid any personalized strategy. It effectively reduced student life to characteristics that were easily measurable and comparable with other students, scoring the student accordingly. McRae (2013) writes about this phenomenon, “[c]omputer adaptive learning systems are reductionist and primarily attend to those things that can be easily digitized and tested” (para. 14). Even with the most sophisticated dataveillance and profiling technologies, higher education institutions will struggle to capture the intricacies of student life that fully illuminate how an *individual* student learns and what exact resources (social, intellectual, or otherwise) a student needs; instead, such analytics will continue to rely on flawed, abstracted “data doubles” (Haggerty and Ericson 2000). So, the rhetoric driving administrators to push “personalized” tools is a paradox: data-driven personalized education will always fail to fully know the person due to a lack of fully comprehensive data. The advising philosophy of getting to know the whole student moves in the direction of personalized education more than data analytics by holding detailed, student-centered conversations with individual students. However, until the student-advisor relationship can be quantified in detail, it is likely that administrators will continue to push for other more easily quantifiable metrics and analytic technologies, regardless of the fact that they privilege poorly developed data doubles over the truly personalizing work advisors strive to accomplish.

6. Conclusion

Staunch learning analytics (LA) proponents argue that big data will transform higher education; however, not all transformations will be positive. The research I described in this article demonstrated some incompatibilities between professional values and norms with big data tools and ideologies. And while my research participants were able to make critical choices that realigned their use of the eAdvising tools with their professional expectations, the findings signal that advisors and, by theoretical extension, other professional groups are under increasing pressure to situate their work practices with data-intensive modes of institutional management. Not all higher education professional communities will retain their autonomy when they begin to feel the effects of contextual suppression.

Like other qualitative research, this study may have limited transferability. While my findings are grounded in reliable, thematically structured data, they are framed by value sets and sociopolitical conditions associated with my case site. It is entirely plausible, for instance, that professional advisors at another institution wholeheartedly embrace advising tools with analytic affordances. With that in mind, the transferability of the “contextual suppression” concept will improve with further research that strategically seeks out particular conditions that lead to suppression, identifies concrete harms brought about by suppression, and pursues negative cases, especially ones that demonstrate how micro contexts experience positive effects from LA tools and initiatives. As such, readers should mark this project as a starting point in a larger, promising and much needed research agenda focused on the particularized consequences of LA.

List of Abbreviations

ASU = Arizona State University

GSU = Georgia State University

LA = Learning Analytics

RCM = Responsibility Center Management

RFID = Radio Frequency Identification

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