How Colonial Continuities Underlie Algorithmic Injustices in Education

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Abstract*—Several aspects of education, including student learning, testing, school assignments, and teacher evaluations are being impacted by a rapid increase in the use of data-driven and automated algorithmic systems. These systems have now come under scrutiny for their discriminatory behaviors that also closely resemble historical injustices. Yet, the research surrounding algorithmic fairness in educational systems conceptualizes this issue predominantly as a technical problem. We claim that there are severe limitations to this approach, especially if we want to shift our focus from the narrow and often problematic definitions of fairness to achieving equity and justice for the marginalized people. In this paper, we argue that the historical injustices perpetuated by these systems are the result of the colonial ways of knowing (and being) that continue to shape them. Our work asserts that in order to progress in the direction of building equitable systems in education, we need to critically examine the assumptions that underlie their design, development, and deployment. Using three illustrative scenarios, we socio-historically contextualize some of the fundamental principles of data and algorithms to reveal that they are still rooted in coloniality. We conclude by inviting researchers to intentionally question their practices and reflect on their position at the forefront of knowledge production on technological advancements in education.

Keywords— coloniality, decoloniality, education, justice, equity, algorithmic fairness

I. Introduction

In the 2014-2015 school year, the school district of Boston (United States; US) adopted an algorithm that individualized school choices based on student's home addresses. The goal was to reduce commute time for the students by assigning higher-quality schools closer to them and in turn, achieve better racial and geographic integration. A 2018 report showed that contrary to the goals, while it did shorten the commute, the automated system led to reduced school integration [1]. As the report suggests, this algorithm was bound to fail, given the inequitable geographic distribution of high-quality schools and the history of racial disparities in placement. Algorithmic systems in education have the ability to entrench historical inequities while obscuring the root cause and automating the effect [2, 3]. Yet, conversations around unfairness in these systems tend to conceptualize this issue as purely a mathematical or engineering problem, often avoiding the needed investigation into the set of values and systems of power that shape them [4, 5, 6]. As the automated and data-driven systems are becoming more widely implemented in classrooms, testing, admission and hiring decisions, school security, and more, it has become necessary to critically examine the principles that underlie these systems [7].

In this paper, we argue that coloniality - often assumed as a thing of the past - continues to shape the technological advancements in education. We believe that many unacknowledged assumptions shaping the design, development, and deployment of these algorithmic systems in education can be tested by historically contextualizing them in colonialism. This is not a metaphorical stance assuming a new and distinct form of colonialism [8]. We push back on the abstract conceptualization of data and algorithmic colonialism that ontologically separates digital resources from natural resources and erases the historical context of present-day structures (e.g., see [9]'s critique of [10]). Instead, we situate the current injustices perpetuated by algorithmic systems within the same system that led to the expropriation of land, body, knowledge, and materials of indigenous peoples and enslavement of others [11, 12]. To illustrate, we present a few scenarios of colonial continuities in current algorithmic systems in education that have direct consequences on students from groups that are historically disadvantaged by colonialism. By taking this stance, we hope to bring the needs of the marginalized peoples to the center [13]. We invite the research community to explicitly question the assumptions surrounding the neutrality and objectivity of data and algorithms and to critically examine the practices that are rooted deeply in colonialism.

II. Background

A. Algorithmic Systems in Education

Education has witnessed a significant spike in the use of automated decision systems. Algorithmic systems can be of many forms - data-driven or rule-based, explainable or a black box, descriptive or predictive. In this paper, we will closely investigate Machine Learning (ML) -based systems due to the rapid increase in their use in education, while our arguments are also relevant to other algorithmic systems. ML models are trained to learn patterns in the historical data that are (assumed to be) representative of the real-world. One of the major goals of ML in education is to enhance student learning using personalized learning systems. ML systems are also incorporated in several other aspects of education like learning management (e.g., Canvas, Google classrooms), testing (e.g., ETS, ACT), exam monitoring (e.g., Proctorio), and teacher evaluation (e.g., Mathematica) - to name a few.

B. The Shift from Algorithmic Fairness to Justice

Contrary to the assumption that algorithmic systems are neutral and rational machines, we have seen several reports of how algorithms manifest serious discriminatory behaviors against those who already face barriers in access to good education [2, 14]. Consider the recent case of algorithmic proctoring software like Proctorio and ExamSoft that gained popularity as the COVID-19 pandemic pushed students to take tests from home. These platforms faced severe backlash from students of color who could not verify their identity, especially for high stake tests like bar exams, due to the poor performance of facial recognition algorithms on darker skin tones. Unfortunately, these are the expected consequences of the standard principles of ML; the models were designed to optimize for overall performance and not fairness. Hence, ensuring fairness in algorithmic decision-making has become one of the major issues in the field lately [15, 16, 17]. The problem, however, is that there is no consensus on what "fair" means - Fair to whom? To answer, we need to take an explicit position on where we, as a society, stand on the social construct of fairness. Is it the benefit of the majority group, avoiding harm to the marginalized people, making systems fair to all groups, or providing justice to historically disadvantaged groups? We also need to define the groups explicitly, which is also not straightforward (e.g., a specific race or gender or sexual orientation, or a specific combination). It has also been shown that it is mathematically impossible to achieve multiple fairness considerations within the boundaries of standard ML principles [18]. What is more unsettling about current fairness definitions is the fact that there is a tradeoff - more fairness constraints will lead to worse performance. In other words, if an algorithm treats someone incorrectly (e.g. denied college admission), the only fairness justification will be that the people from the dominant group were also treated equally incorrectly. Quantifying fairness definition is not new to education - from 1964 to 1973, a similar effort was undertaken by educational assessment researchers without fruition [19]. Other simple approaches like excluding race in the data to avoid racial bias also do not work. Bias is embedded in data more intricately due to historical reasons. For example, in the US, zip code is highly correlated with race. We believe that this conversation needs to shift from fairness to equity. Instead of making data race-less, we need to acknowledge the history of racial inequities, and shift the requirement from reducing harm to providing justice [20]. For this, we need to think beyond what is possible mathematically.

C. Coloniality and Decoloniality

Data and algorithms in education do not exist in a vacuum but are developed and implemented by humans in a real context. Our work claims that a socially just approach to technological advancements should begin with an acknowledgment, articulation, and rejection of historical colonial roots that inform present-day practices. Importantly, we first acknowledge that not all colonial structures operated in the same way; history, location, and geography matter when considering the impact of coloniality [21, 22]. The term *coloniality* captures the operations shared by differing colonial systems - that is, the enduring "logic, metaphysics, ontology, matrix of power created by the massive processes of colonization and decolonization…[that] can continue existing after formal independence and decolonization [23]." Coloniality is therefore what lies in the wake of colonialism, that which "seeks to explain the continuation of power dynamics between those advantaged and disadvantaged [24]." Our work asserts that before the work of decoloniality can begin in algorithmic systems in education, we must first recognize the claim that control of land, bodies, and, in our current present, data, are part of the legacy of colonial structures, and this recognition is only the beginning. If coloniality is about the historicization of prior legacies of colonialism, then decoloniality aims to contextualize that history, towards process and fundamental purpose, in order to "thoroughly challenge the colonial situation [25]."

III. COLONIAL CONTINUITIES AND ALGORITHMIC INJUSTICES

In this paper, we argue that the historical injustices perpetuated by algorithmic systems in education are the result of the colonial ways of knowing (and being) that continue to shape them. We investigate the colonial roots of the unacknowledged and often ignored or overlooked assumptions underlying the design, development, and deployment of these systems. One possible objection to our stance could come from the argument that colonialism has ended and so has its impact on this world. To this, we would like to quote Loomba [26] - "...if the inequities of colonial rule have not been erased, it is perhaps premature to proclaim the demise of colonialism." Another counterargument to our position can come from the ideological standpoint that we have already decolonized our knowledge, history, and culture and that algorithmic oppression is a new form of colonialism that tries to expropriate human lives (even that of historically privileged people) through digital data (e.g., [10]). We would argue that such a stance uses decolonialism as a metaphor - the kind of which indigenous scholars like Eve Tuck and K. Wayne Yang [8] strongly warned against. Instead, we believe that these present-day oppressive structures exist because of the actual histories of colonization. Thus, we examine algorithmic injustices by historicizing them in colonialism. Lastly, there could be questions about feasibility - how practical is it to question all our assumptions? We agree that this is not an easy endeavor. But, so were all the struggles for freedom from European empires. As Fanon puts it, "Decolonization which sets out to change the order of the world is, obviously, a programme of complete disorder." Moreover, isn't the code of order the very principle that regulated and legitimized colonial practices in the first place [27]? In the rest of this section, we argue for our position with three illustrative scenarios that map current algorithmic practices to its unsettling colonial roots.

A. Measurement and Reality

At the foundation of any algorithmic system is an operational definition of the phenomena being modeled - a need that often requires reducing the social world into issues of measurement. The world is understood by the aspects of it that can be quantified, measured, and standardized. The rest is ignored, made irrelevant, or assigned for "future" research. Let's consider the example of predicting student dropout - studied in various educational settings like college enrollment, academic courses, and Massive Open Online Courses (MOOCs) [28, 29]. The measurable characteristics of student activity (e.g., time taken to answer a quiz, number of hints used, average number of posts in the discussion forum, etc.) define who an individual student is with respect to their tendency to quit. Students are compared to one another to identify the characteristics differentiating a quitter from a non-quitter.

We argue that the unquestioned assumptions on the validity of this approach stem from the same Western worldview that drove colonial research practices of classifying indigenous societies into categories, simplifying them with a system of representation, comparing, and evaluating them to be ranked [30]. In what tried to be an objective and neutral positivist approach, was the deeply rooted cultural orientation, value system, structures of power, competing theories of knowledge, and conflicting concepts of fundamental things like time, space, and subjectivity [12]. The result of such measurement and reporting back was an understanding of indigenous people, their land, and societies that were radically transformed to fit the Western discourse. At the core of the colonial ideology of legitimation is the assumption that Western ideas (assumed to be innately superior) are the only rational way of making sense of the "reality". Other ways of knowing (and being) in the world are delegitimized and disavowed.

Most data-driven and automated algorithmic systems in education hold a similarly narrow interpretation of the (social) world in which students learn. Furthermore, such technologies are likely to be used in under-resourced schools as a fix or rather an excuse against deeper investigations into the sociopolitical problems of the educational system [7, 31]. Going back to the example of student dropout prediction, an individual student is represented with a narrow set of measurements for the decision-making machine to process. There is no consideration of the inequities that correspond to the disproportionate rates of dropout in certain student populations. There is also a tendency, in general, to discuss some of these differences as a deficit [32]. Our stance in this paper is rather that of Ladson-Billings' when she says, "We do not have an achievement gap; we have an education debt." When discussing the disparities in the educational outcomes of Black, Latina/o, and Native American students, Ladson-Billings concludes that there is a historical, economic, sociopolitical, and moral debt owed to students whose identities were treated as barriers in the educational system. The debt, she argues, is not about what we might mitigate, but what is owed after years of undeserving them.

B. *The Farther, The Better*

As elaborated by Tuhiwai Smith in her book *Decolonizing Methodologies* [12], in direct opposition to indigenous worldview was the Western lineal views of space and time - with systems of language making them "real", static, and well-defined. Such an orientation represented native people as indolent (lacking in organizing time) and claimed an "ideological position of dominance" over native land (the space to be tamed). It also supported the notion of progress in the name of colonialism as measured by (narrow definitions of) technological advancements. To be measured, space had to be compartmentalized and categorized (e.g., school vs home, physical vs psychological space) and so did time (e.g., early modern vs late modern). It was easy to draw boundaries. We argue that this western worldview of space and time is central to some of the fundamental assumptions in algorithmic systems in education. The measurement of student activity is typically confined to the boundaries of the controlled learning space (e.g., a physical classroom, an online tutor, a MOOC platform). Space was assumed to be divorced from time, allowing colonizers to depoliticize it and justify the erasure of historical injustices. It is ironic that these algorithmic systems are built on historical data (e.g., college success of past students) but conveniently restricts the period and aspects of the history (e.g., systemic racism in the admission and hiring process). Embedded in institutional practices, these ideas determine what is and who is legitimate. Where then is the place for alternate worldviews, especially if it does not fit the dominant ways of knowing?

More importantly, this worldview introduced and sustained the concept of distance. "Through the controls over time and space the individual can [also] operate at a distance from the universe" [12]. Distance separates those in power from those they control - making the whole endeavor impersonal and highly effective. It also allows for implied objectivity and neutrality on the part of the outsider making decisions for the lives they control. We argue that algorithmic systems add to this distance by further separating the people who design them from the people whose lives are impacted by them [33]. Consider the social, cultural, and economic distance between the lived reality of an economically marginalized Black student in a Harlem (US) public school and that of current designers of educational technology in Silicon Valley. How well can the designer assess the needs of this student and embed them in the goals and purposes of the technology that will go into their classroom?

This is further exacerbated by the recent trends in using relatively cheap and readily available out-of-the-box predictive systems provided by companies like Amazon, Microsoft, and Google who often don't have control over their downstream application. For example, facial analysis toolkits used for automated attendance or security purposes in schools are not designed to work with students wearing a face-covering like a niqab. There is a common saying in ML - "Models are always wrong, the question is whether they are right enough to use." Our question here is - "right enough" for who? Who is considered and who is left out in this decision? In building predictive systems, it is a common practice to estimate its generalizability by testing the model on unseen data. The issue, however, is that the unseen data is usually part of the same dataset (same population) but kept out while training the model. Yet, the generalization estimate is accepted as the true estimate of the model's performance in the "real world". Since collecting data in all scenarios of potential use is difficult or in some cases impossible (e.g., the admission office only knows the GPAs of the students who were previously admitted to the institution), this estimate may not hold with the non-dominant population.

C. *Normal versus The Other*

In the third scenario, we try to view the impact of colonialism more closely from the perspective of those who were colonized. Through economic expansion, promotion of science, and subjugation of "Others", colonialism realized the European imagination of new worlds for the "modern" human people [34]. The settler interests surrounding wealth and class status dominated the politics of the colonies. Within the image of the future modern nation was the image of the "Other" defined by stark contrasts and subtler nuances to justify how indigenous communities were perceived and dealt with [12]. Systems of classification (e.g., hierarchies of race) were used to rationally explain the negations on indigenous people and their systems - not fully human, not civilized enough, not literate, and inadequate languages [35]. The result was a systematic fragmentation and erasure of colonized societies - their histories, ways of thinking, relationship with their land, and social relations [25, 27]. Interrogating the colonial roots of normalcy could help us identify who/what is dispossessed in data and algorithms, and in the name of whom/what [9].

Recognizing parallels between the actual history of colonialism and our present-day technological choices is not so hard [36, 24]. Algorithmic systems often reflect a normative vision of the world. A new "data sample" (e.g., a student in reality) is classified based on how well it fits (or not fits) the model - is it normal or is it an outlier - the other? Whittaker [37] questions the underlying assumptions in this approach - "What "norms" are produced and enforced by AI systems?...what are the costs of being understood as an "outlier"? [37]". The idea of normal versus "Other" manifests in specific ways in the modeling process leading to unfair algorithmic systems. First, the data of the "Other" group is likely to look different from the dominant group. For example, differences in skin color, facial features, or expressivity of different emotions in the data used to train a student emotion detection model [38]. Second, the "Other" group is likely to be underrepresented in the data (e.g., number of native American students in higher education). Third, the predictors designed may be less predictive for the "Other" group. For example, high school club or sports team participation as the predictor of college success when some students either could not afford it or had to work jobs to financially sustain their family. In all these cases, by picking a model that is optimized for the overall performance, it is highly likely that we compromise on its performance on the "Other" group causing significant harm to those who already face barriers in education (e.g., denied college admission, fired teachers in low-resource public schools (Mathematica [39])).

Several recent studies have investigated discriminatory decision-making by algorithms; more often than not they enforce norms that further marginalize the group that doesn't fit the dominant "normal" narrative. Examples include unreliable emotion detection on dark-skinned students [40], Black vernacular marked as toxic by hate speech detectors [41], and encoding bias against certain linguistic and ethnic groups in automated essay scoring [42]. Yet, these systems continue to be deployed in the name of efficiency and cost-saving. Decolonial thinkers critique the notion of progress in terms of power and emphasize the role of race as the naturalized, hierarchical exclusionary criteria in the production of knowledge by colonial modernity [34]. Let's take the example of cameras, the technology that produces all the data (e.g., images, videos) for applications such as student emotion recognition through facial expression and gesture analysis. Now consider the fact that earlier cameras were designed to bring out high contrast and better resolution for white skin color [43]. Technology is an engineered human artifact and the technological choices do favor or disfavor certain groups based on the power structures. As technology continues to get embedded in education, we need to ask before and during design - whose interest is our technological choices serving?

IV. CONCLUSION

The condition of coloniality in contemporary societies can be witnessed through the social discrimination resulting from the continuing legacy of colonialism in social orders and forms of knowledge [44, 36]. In this paper, we argue that to understand and tackle historical injustices perpetuated by algorithmic systems in education, we must investigate how coloniality continues to shape these systems. We contend that some of our fundamental assumptions rooted in colonial epistemology and ontology need to be questioned and critically examined. To illustrate, we foreground the sociohistorical context of some practices in the design, development, and deployment of these systems. To progress in the direction of equitable systems, we must first acknowledge the limitations of the purely technical fixes that are dominating our current conversations. Consider the example of increasing representation by collecting more data. This may not be in the best interest of the marginalized people - especially when it comes at the cost of increased surveillance and compromises on privacy and individual agency. One way to assess how power structures are shaping our technological choices is to reflect on questions such as: Whose knowledge is progressing? Whose voices are included in decision making and more importantly, whose voice historically has not been?

Once we recognize and acknowledge colonial continuities in algorithmic systems that are exacerbating injustices in education, decoloniality must follow. Decoloniality aims its "efforts at rehumanizing the world, to breaking hierarchies of difference that dehumanize subjects and communities. [23]" We also warn readers to be wary of the abstract conceptualizations of data or algorithmic colonialism that erases the actual history of colonization and co-opts the term decolonization to define new forms of colonialism [45]. Instead, we need to recenter the narrative on lived experiences of communities historically and continually disadvantaged by colonialism, which is now further worsened by algorithmic systems. Hence, it becomes essential that our practices are informed by the recommendations from these communities. For instance, several indigenous-led movements are working for better data governance, ownership, and data sovereignty. This includes Global Indigenous Data Alliance (GIDA), the Local Contexts initiative, and US Indigenous Data Sovereignty Network (USIDSN). Our data collection and analysis for algorithmic systems in education need to align with the frameworks emerging from such spaces.

As a research community, more broadly, we need to make way for alternative worldviews and epistemologies, and new methodologies to come to the center, and make a place for indigenous scholars in our community to write, theorize, and research as indigenous scholars (e.g., the anti-positivist approach of Kaupapa Maori research; [12]). Eve Tuck and K. Wayne Yang [38] warn us against the opposite effect of decolonization wherein the "...settler intellectual who hybridizes decolonial thought with Western critical traditions (metaphorizing decolonization), emerges superior to both Native intellectuals and continental theorists simultaneously." Our efforts must only strengthen the indigenous research agenda of self-determination. So, yes, this requires many of us to displace our own power. But we believe that this is the moral obligation of our current positions at the forefront of knowledge production in technological advances in education. In this work, we have attempted to historicize and contextualize the present-day continuance of coloniality. We have yet to undertake the more difficult work of decoloniality, in which our attempts to rehumanize the world are just beginning.

POSITIONALITY

First Author (she/her) - I belong to the *Kodava* tribe of Southern India. We worship nature and our ancestors. Our native tongue is an endangered language without a writing system. I was born in the *Chodumada okka* (family group) and married with the *Mukkatira okka*. I am a first-generation college student currently residing in the US as an international student. I am a learning sciences Ph.D. candidate with ten years of experience in computer science and ML, including five years in the technology industry. I research applications of ML in education. I design, develop, and research data-driven algorithmic models of student affect, behavior, and cognition.

Second Author (she/her) - I am an African-American woman of mixed background who profoundly asserts her Blackness. I speak African American English and other varieties, as well as French and some Arabic. I was the first in my family to earn a Ph.D. and I am a former McNair Scholar and Mellon Fellow. My research analyzes pedagogical practices of settler colonial education that persist in present-day teaching practices. I am a descendant, believer, wife, and mother of two.

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