Big Data and Educational Justice

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Introduction

Information and communication technologies (ICT) have the potential to revolutionize the educational landscape, in a way that has far reaching ethical implications. This paper examines the possible effects that big data technologies have in terms of distributive justice.

Distributive justice is the study of the desirable moral principles that should guide the allocation of benefits, resources and costs in society. In the educational context, it explores questions such as how educational resources should be distributed, whether it is just that children from different social class (or cognitive ability) have different educational outcome; and what does justice require in terms of children with disabilities. Philosophers differ among themselves with regard to the principles of justice they adopt with regard to the educational sphere, and the desirable balance between requirements of educational justice and other values such as parental rights, the nurturing of educational excellence, and others.

The philosophical debate concerning educational justice purports to have practical implications. The principles of justice offer a moral evaluation of education policies and reforms such as school choice, private schools, and the reform that is the focus of this paper – the incorporation of ICT in schools.

This paper explores the effects of ICT on distributive justice in education. It starts with a short description of the classroom in an era of big data: students are equipped with electronic devices that provide them the lectures and educational material. Educational software assigns students with tasks according to their level of ability and evaluates their progress, and students can conduct further research and independent study. Interaction between students and their teachers, and among themselves, is also facilitated through educational software, enabling group discussions and cooperation.

As a side effect of these activities, learning systems generate a vast amount of granular data about students including their performance on tasks, time on task, physical

indicators, queries on search engines and content of communications in group-discussions and emails. Data mining technology analyzes the data and informs decision-making at all levels: the specific student, the class, the school, and at policy level.

After setting the stage, I move on to examine four issues that are affected by ICT and are central to discussions of distributive justice.

The first concerns scarcity of resources. ICT, I argue, decreases scarcity in teachers and their time, because many of teachers' most time consuming tasks are now performed electronically. However, the problem of scarcity of resources is not resolved by technology, rather, ICT merely shifts the problem from the distribution of quality teachers to the distribution of computers, software or technical support.

The second issue likely to be affected by the technological revolution, and specifically by the use of big data in educational decision-making, involves the positional nature of K-12 education. Education's instrumental value, as a means to securing rewards such as access to higher education or the job market depends, largely, on the students' relative position compared to other students. When a candidate is seeking a job or a spot at a prestigious university, what matters is not the objective quality of her education but rather whether the other candidates' educational credentials are superior to hers. Education's positional nature has import for the requirements of justice suitable for education. More specifically, it grounds a requirement for educational equality. Basing assignment and hiring decisions on big data decreases the positional dimension of education because it takes into consideration a wide array of other attributes rather than just formal educational credentials. As a result, the requirement for educational equality may lose some of its justificatory thrust.

The third issue I address involves peer effects, namely the influence that the level of ability of one's peers has on educational achievement. The peer effect is central to the discussion of educational justice, adding requirements such as integration to the more traditional discussion of resources that dominates distributive justice in other domains. Interaction between teachers and students, and students among themselves will undergo major change with the adoption of ICT in education. On the one hand, it is much easier to accommodate students with different abilities in one classroom, because students sitting side by side can engage in quite different tasks. At the same time, however, the modes of

interaction between students is arguably less robust than those in the 'traditional classroom', plausibly decreasing the effect that peers have on one another. If the effects are still relevant, they may pertain to online peers rather than other students who are physically present. This may require rethinking some of our assumptions when designing principles of justice in education.

The fourth and final issue I address in the paper concerns biases in educational decision-making. Biases and discrimination in educational decision-making are an age-old problem that constantly accompanies educational decision-making. The use of big data for educational decision-making has the potential to decrease biases (because it is, supposedly an objective method that bypasses human decision making which is notoriously biased. However, it also raises some concerns in terms of biases and discrimination. Algorithms rely on previous, human, decisions in order to make their predictions therefore they may reinforce existing biases. Additionally, algorithmic decision-making can create new challenges in this regard, because of the kind of data it has access to and its limitations.

The conclusion of the paper is that alongside other aspects of big data, its effect on educational justice is likely to be significant, and should be taken into consideration when designing its application and discussing its merits.

The classroom in the big data era

Think of our traditional classroom, one like most of us sat in as children. The teacher, stood at the head of the classroom and lectured to the students about a certain subject – history perhaps, or science. Students were required to listen, take notes and answer questions when asked. The teacher assigned tasks and tests, which she then graded.

Now think of a classroom in the technological era, already a reality in some schools: each student has her own personal device, equipped with an educational management system. Students access modules assigned by the teacher in which the course material is delivered through audio and visual means – presentations, films, or animation. Since the modules can serve many thousands of students, the investment in creating high quality materials is reasonable, so the best lecturers are cast, using appealing graphics and illustrative examples that relate to students' worlds. Students can watch these modules at their own

pace, in class or at home, as many times as they need, returning to specific parts as necessary. Each module can also have links to additional information for enrichment, or explanations on specific issues that may be harder to understand.

The Ed-tech revolution, however, involves much more than merely watching recorded videos of teachers. Learning management systems (LMS) assign individually tailored tasks to students, according to their pace and level, and evaluate them. Teachers can supervise this process in real time, and assist students when necessary. The LMS also facilitates interactions between students, enabling ad-hoc discussion groups or chats, and creating multiple possibilities for cooperation, peer-learning and peer-evaluation, even between students who are not physically in the same classroom (or school). Teachers can also interact with their students through the system using emails, instant messaging, or taking over their device, according to what is most effective in the specific situation.

Interactive digital educational tools, such as those mentioned above, generate immense amounts of granular information about students. This data – "big data"[1] – includes not only consciously disclosed information, such as entries concerning grades, behavior and attendance, but also metadata concerning the students' online activity. Moodle, for example, is a popular LMS that can be used for task assignments, quizzes, content delivery, and communication. Moodle logs students' every keystroke – view and download commands, start and end time, time on task, and correctness (Krpan & Stankov, 2012). Although not yet operational in most systems, applications that can monitor bodily movements and indicators such as heart rate, eye movement, and facial expressions already exist, and can provide data concerning students' physical reactions while performing educational tasks (Effrem, 2016).

In addition to the data collected from educational computerized platforms, further data concerning students can be made available. Student ID cards may collect data on activities outside the classroom such as purchases in the cafeteria or library loaning logs. Schools may also collect information about students from non-educational sources, like social media or email accounts.

To make sense of the quantity and diversity of data, educational data mining (EDM) technologies are used (Baker, 2010; Baker and Siemens, 2014; Castro et al, 2007; Baepler & Murdoch, 2010). Data mining finds unexpected correlations and patterns

connecting students' attributes, habits, and attainment, thus offering insights concerning learning processes and pedagogy. Algorithms analyzing big data, it turns out, are extremely successful predictors of any designated attribute, such as dropping out, educational success, and effectiveness of programs. Therefore, they can help identify which students need help; can inform educators which pedagogical methods support learning and which inhibit it; can evaluate teachers and courses, and can examine education systems as a whole – their efficacy and equity (Federal trade commission, 2016; Prakash et al, 2014; Reid-Martinez and Mathews, 2015).

Within this educational setting, teachers have a different role than they had in the traditional classroom. Freed of some of the most time-consuming tasks they had to perform, they will be able to focus on aiding students that require help, on ensuring the social and emotional wellbeing of students, and on overseeing the decisions of algorithms and software. They need to develop technological competence in order to make the most of the opportunities that technology presents them, and to be able to troubleshoot minor technological problems. Alongside teachers, other professionals will increasingly take center stage: educational software designers, algorithm designers and computer technicians will all be extremely involved in the everyday operation of schools.

Big data and educational justice

Educational reform and changes in social circumstances often have effects in terms of distributive justice. One of the most important roles of educational justice theory is to evaluate and critique social reality and education policy in terms of their influence on justice. I argue that the implementation of ICT in schools is likely to bring about significant changes in terms of educational justice. This change cannot be easily characterized as improving or worsening the situation in terms of educational justice. it involves, rather, opportunities for improvement alongside new concerns. Moreover, I argue that some of the expected changes to schools run deeper than others. These changes will require more than just evaluating whether they promote educational justice or not; they may change the way we think about educational justice more fundamentally.

In order to substantiate these claims and characterize the changes in terms of educational justice, I now discuss four issues that are central in terms of justice and are likely to

change in an era of big data: scarcity of resources; education's positional nature, peer effects, and biases in educational decision-making.

Scarce resources

One of the most fundamental factual assumptions incorporated into discussions of distributive justice in general, and distributive justice in education, more specifically, is the assumption of scarcity. Scarcity is, to a large extent, what motivates the discussion; we think about schools in which there are not enough resources to ensure adequate facilities, science labs or even books for all students, and we think of students who are failing because of this shortage. The blanket, we know, is too small; we must prioritize; and the decision to invest in one worthy cause entails withholding resources from others.

Principles of distributive justice aim to guide us in the excruciating task of allocating insufficient resources: how much should we direct toward improving the educational outcome of children from poor background? How should we treat the additional needs of children with disabilities? Are we allowed (or required) to invest resources in programs for children with high ability? If we had enough resources, and we weren't compelled to choose between the different causes, the debates concerning educational justice would significantly change.[2]

Educational technology, clearly, cannot overcome scarcity of resources. It will not, for example, alleviate whatever shortage exists in school buildings, lunches, and transportation to schools. But it is likely to significantly alleviate the scarcity in quality teachers and their time, which is currently one of main sources of inequality in schools. Teachers are expensive – their salaries comprise a huge share of education budgets – and they can only serve a certain amount of students effectively, making the ratio between teachers and students an important indicator for the quality of education. The allocation of teachers both in terms of quantity (teacher-student ratio) and in term of quality (where and which students do good teachers teach) is usually unequal. Schools that serve low-income students are significantly more likely to employ unlicensed teachers, teachers that teach outside their area of expertise, and to suffer from a high turnover of teachers (Peske and Haycock, 2006; Frankenberg, 2009).

The technological revolution will, arguably, decrease the scarcity in teachers and teachers' time. As was discussed above, teachers' time is likely to be invested in the technological era quite differently than it was in the traditional classroom. The most time consuming tasks for teachers in the past – preparing for class, teaching, writing tests and grading them – are performed largely be computerized systems. Teachers are able to devote more time to personal attention to students and monitoring their progress using the output of computerized systems. They can coordinate group discussions and respond to questions, and see to the social and emotional wellbeing of students. And while the teacher still has, by all means, a lot on her plate, a significant load is taken off her shoulders and her time becomes a less scarce resource.

Not only will teachers and their time gradually become less of a scarcity, ICT will also be able to decrease inequality in the allocation of good teachers between schools. Students using online resources described above have access to high quality pedagogy (through the videos and presentations created for general use), even if the teachers who are physically employed at their school are inexperienced or inadequately trained.

Another change likely to occur in terms of resources is that the need for pull-out programs for children with either above or below average abilities will decrease. Although some of the justifications for these programs may still remain (the importance of social interaction with children with similar abilities, perhaps), the argument according to which the 'regular' classroom cannot accommodate children with different abilities will be contended with through personalized learning. Advanced programs can become much more accessible to students, much like higher education has become more accessible due to MOOCs (Massive Open Online Courses). Once schools will be better equipped to address the different levels of ability of its students, resources traditionally directed to creating the infrastructure for programs for children with especially high or low abilities will not be needed.

ICT, however, does not solve the problem of scarce resources. It merely shifts the problem to other places. Teachers working in the technological classroom will require new skills in order to make use of the opportunities that technology offers. Poor schools will still, most probably, be allocated the teachers that are least capable in performing these new tasks.

Additionally, there is no reason to assume that technology (hardware – computers, tablets, network connections; and software – educational management systems, quality educational content) will be dispersed in schools universally and equally. Given the impoverished state of some schools that lack the resources to ensure even a steady supply of toilet paper, implementing cutting edge technology may seem a distant dream. Because technology is constantly developing, it quickly becomes outdated, so the investment in educational technology must be ongoing and schools serving disadvantaged children are unlikely to be able to keep up. Ensuring adequate and equal technical support is another crucial component of computerizing schools, because frequent malfunctions are to be expected.

Therefore, although teachers and their time are likely to lose their centrality as indicators of educational advantage, the dilemmas of distributive justice that stem from insufficient resources and multiple needs are unlikely to go away.

Education as a positional good

In the previous section, we discussed how technology can change the kinds of educational resources that are scarce, and the kinds of resources that abound. Educational injustice, however, is not caused only by shortage in objective resources, but also by the existence of relative educational disadvantage – by the fact that some children have a better education than others (Brighouse, 2010; Harel Ben Shahar, 2016). Relative disadvantage is unfair, arguably, because education is a positional good, meaning that its value is determined not only according to the objective quality or amount an individual has, but also comparatively. Education plays an important sorting function in society, determining access to further rewards in life such as lucrative jobs and higher education. The kind of rewards education can grant access to, depends on the comparative quality of one's education. If other candidates for the same job have better educational credentials than you do, your education has low value, whereas if your competitors have inferior credentials, your education is more valuable, and will grant you the desirable position.

As a result of education's positional dimension, contending with objective scarcity is insufficient in order to fully address educational justice. Increasing resources cannot solve the "socially scarcity" as Fred Hirsch (1977) calls it, because even if the objective

level of education rises, as long as inequality persists, disadvantaged children will not have better access to socially desirable positions.

MOOCs demonstrate this point. MOOCs revolutionized the access to higher education, enabling unlimited numbers of individuals, from anywhere across the globe, to gain what was previously limited only to a privileged minority. While widening access to higher education is clearly immensely valuable for society and for individuals, we should keep in mind that higher education, like K-12 education, is positional, namely it is instrumental in securing further, competitive, rewards (primarily jobs). Removing barriers to obtaining educational credentials triggers a process in which the market devalues those same credentials, making further or better credentials indispensible for gaining the same objectives (Collins, 1979). Employers are therefore likely to quickly adjust their hiring practices to respond to the growing prevalence of degrees, for example by attributing less value to MOOCs compared to traditional degrees.[3]

Positional arms races like the educational arms race have been found problematic from a moral perspective: they are inefficient, because they force individuals to obtain further educational credentials that are objectively unnecessary merely to sustain their relative standing; they are also unfair because when an individual gains educational advantage he pushes others back in line, denying them access to the reward (Brighouse and Swift, 2006; Halliday, 2016; Harel Ben Shahar, 2017). These problems have led several philosophers to rely on education's positional character as a central justification for promoting educational equality (Brighouse, 2011; Harel Ben Shahar, 2016).

However, big data technology could, potentially, decrease the positional nature of K-12 education.

Decreasing the positional nature of a good ("de-positionalizing") can be achieved by changing the way the reward is distributed (Goodin, 1990; Halliday, 2016, Harel Ben Shahar, forthcoming). Thus, if jobs and places in higher education were less competitive, or would not rely on high school achievements, K-12 education would cease being positional, or would be less positional. For example, admission policy to higher education or employers' practices could be changed, prohibiting employers from publicizing educational requirements that exceed those necessary for the job. Another possibility would involve adopting random admission policies for higher education (perhaps setting

a minimal threshold). Reducing positionality could also be achieved by introducing a wider range of selection criteria in addition to K-12 achievement thus making K-12 education less weighty in the decision. All of these decrease the positional nature of K-12 education by granting it less weight in the allocation of competitive future rewards.

Big data is already reforming admission policies in higher education institutions (Felton, 2015), and involves using diverse kinds of information concerning candidates. Educational track record (such as grades, enrolment in advanced placement (AP) courses, attending a selective private school, and so on) is still, of course, part of the data fed into the algorithm, but it is not the only component, or even the most important one. A myriad of other types of data can now be factored into the decision, including online consumer habits, searches on search engines, health indicators, activity in social media, and much more. And importantly, big data arguably grants admission committees better predictions of student success and retention than any existing method (Goff and Shaffer, 2014). Reducing the weight given to students' achievements in school entails that inequality in K-12 education is less destructive to an individual's life prospects than under traditional higher education admission policy. Note that educational credentials are not replaced by any single alternative dominant attribute (which would thus become the positional good responsible for distributing the reward), but rather the decision is based on the integration of multiple factors, each having a relatively small effect on the decision.

There are, however, several possible doubts concerning the argument that big data decreases education's positionality. First, although algorithms now incorporate many different attributes, some of them might correlate one another, and the original attribute is therefore still dominant. For example, online shopping habits plausibly correlate socioeconomic class, and therefore taking shopping habits into consideration in an algorithm entails giving class extra weight. As a result, big data can only decrease K-12's positional nature if the additional attributes it takes into consideration are not proxies for success in K-12 education.

Another issue involves the kinds of data that admission committees take into consideration. Because of ICT within schools, students' educational data is so plentiful that it can supply sufficient information for algorithmic analysis even without adding non-educational data. If the kind of data that is used is all created within schools, then K-

12 education will remain positional, although it may alter the definition of "achievements". Grades might stop being the most important thing in determining one's chances of being admitted to higher education, and algorithms may find that learning habits, level of concentration or time on task, as recorded by LMSs, or behavior and attendance, are better predictors of success. Be that as it may, as long as school related data is the dominant determinant of admission to higher education, K-12 education retains its positional dimension.

Employers, like admission committees, are also beginning to use algorithms that analyze big data to guide their hiring decisions (Walker, 2012). Whitetruffle, a San Francisco based start-up, offers employers recruiting services based on an algorithm that takes into consideration a combination of tens of attributes instead of the regular categories of education and employment history (Markowitz, 2013). LinkedIn also uses algorithms for supporting hiring decisions: the algorithm learns the preferences of its recruiter users, by suggesting "people you may want to hire", based on previous clicks and hires. This algorithm, too, takes into consideration multiple attributes instead of focusing on educational credentials and occupational history. Doing so decreases the stakes in K-12 education, and educational disadvantage can be offset by other attributes that are incorporated into decision.

De-positionalizing K-12 education through big data may require theories of educational equality for which positionality serves a justificatory role, to rethink the desirable principle of justice in education. And although educational inequality may be objected to on other grounds, removing positional disadvantage alleviates one of the most morally abhorrent consequences of inequality in education.

Peer effects and integration

The third issue I wish to introduce into the discussion involves peer effects. The communicative nature of education entails that rich and stimulating interaction between students and between students and their teachers improves educational achievement. Learning with high ability peers, therefore, has a positive effect on attainment, and separating students with low ability into homogeneous classes disadvantages them because of the loss of positive peer effects.

Academic sorting disadvantages students with low ability not only because of peer effects, but also because it causes racial and class segregation, which can be seen as discriminatory. As a result of various reasons, academic ability correlates socioeconomic class and ethnicity (Ross and Kena, 2012; Skiba et al, 2002; Garda, 2005, Knotek, 2003). Thus, children from poor families, racial minorities and other excluded groups are overrepresented in lower tracks and in special education, whereas children from privileged families are overrepresented in higher tracks and in gifted programs (Oakes, 1995; Greene, 2014; Cipriano-Walter, 2015; Solorzano and Ornelas, 2002; Erwin and Worell, 2012).

Because of the importance of peer effects in determining the quality of education, and the correlation between academic ability and other classifications such as race and class, student assignment is often a linchpin in struggles for educational justice. Affluent parents who wish to avoid integration use various means to do so – private schools (Chubb and Moe, 1990; Clotfelter, 2008); moving to the suburbs (Clotfelter, 2008) or to a neighborhood with a good school (Downes and Zabel, 2002); religious education (Harel Ben Shahar and Berger, 2017); specialized education (Minow 2011; Garcia 2010; James 2013) and ability grouping (Oakes, 1986; Biafora and Ansalone, 2008).

Educational technology, of the kind described above, may change the way peer effects are manifested and as a result alter the normative approaches toward integration. In a technological era, students sitting side by side in the same classroom are assigned different tasks, according to their abilities, and students can participate in online discussions or working groups with students who are not physically present. This alleviates the difficulties teachers face when teaching heterogeneous classes and suggests that mixed ability classrooms may be easier to sustain: students of varied abilities can sit next to each other, have social interactions, and yet each can be supplied with teaching that is tailored exactly to their needs. According to the traditional working assumptions of educational justice – namely that integration is good – this would be marked as a positive development.

On the other hand, it might be the case that the modes of learning in the technological classroom decrease the significance of peer effects. If students do a considerable share of learning on their own, interacting with educational software instead of with peers and

teachers, then it is likely that peers will not influence educational achievement as they did previously. And even if peers remain significant for educational achievement, the relevant peers may be those that students interact with online and not those who are physically on site.

School integration is valuable, however, not only because of peer effects. In her 2010 book, *The Imperative of Integration*, Elizabeth Anderson argues for a more general moral duty of integration (in education and beyond) that does not hinge on the consequential argument concerning peer effects. According to Anderson, integration is crucial for creating the kinds of social relations that can sustain democratic equality and to prevent relations of subordination.

Whether or not the relations between students in the future classroom can foster the kind of relations required to create social solidarity discussed by Anderson is yet to be seen. Hopefully, students will continue to interact, socialize and play in school, thereby creating the type of relationships that underlie democratic equality. And if the use of ICT in schools hinders the development of meaningful social relationships, this calls for a much wider alarm that reaches far beyond the concerns of distributive justice.

Biases and Discrimination in Educational Decision-Making[4]

For years, educators have been troubled by persistent implicit biases in educational decision-making, directed against children from racial minorities, children from poor families and girls, thus aggravating educational injustice that originates from social circumstances. These biases that teachers unknowingly have taint their evaluations of students abilities and behavior and affect their interactions with them. Since implicit biases are hard to dismantle, it has been suggested that the use of algorithms to inform educational decision-making, and especially assignment decisions can potentially decrease biases and promote objectivity (Har Carmel and Harel Ben Shahar, 2017).

Extensive research on the effects of algorithmic decision-making on student assignment is yet to be conducted, however encouraging findings in one study suggest that algorithmic decision-making concerning student assignment is indeed less biased than traditional decision-making performed by teachers. The study examined an LMS called EVAAS,[5] that was used in order to determine assignment of eighth grade students to

different levels of math courses. Teachers participating in the study reported that the algorithm assigned students to a high track that would otherwise not have been identified as suitable for the program. It also increased shares of children from racial minorities and low socioeconomic status in the high track without reducing students' success rates (Dougherty et al, 2015).

Algorithms, however, are unlikely to completely solve the problem of biases in educational decision-making, and may, in fact, create new challenges in this regard. Algorithms train on historical datasets, using them in order to learn which attributes (and combinations of attributes) best predict the relevant outcome. Thus, an algorithm meant to inform university admissions will analyze the attributes of successful graduates, and will evaluate applicants according to their compatibility with that model. Relying on historical datasets runs the risk of perpetuating former biases that pervaded traditional assignment decisions. Historical racial prejudice, or racial imbalance caused by social disadvantage will be replicated through the algorithm's predictions.

The possible discriminatory effects of big data have already been recognized in several fields such as banking, insurance, and law enforcement. Thus, individuals from racial minorities are likely to be profiled by algorithms predicting involvement in crime, resulting in increased police surveillance and arrests. They are also more likely to be identified as high-risk consumer of insurance policies and high-risk debtors leading to higher premiums and interest rates (Barocas and Selbst, 2016). Similar effects in educational decision-making are likely.

Additionally, while discussions of distributive justice primarily focus on groups that are traditionally disadvantaged and discriminated against – racial minorities, individuals with low income, people with disabilities – other groups may also be disadvantaged as a result of algorithmic decision-making. The use of big data technologies in education and beyond could form new categories of individuals who are systematically disadvantaged. It has already been recognized that big data has its "exclusions" – individuals and groups who are not properly represented in the data (Lerman, 2013). In a world in which governments and businesses are increasingly relying upon data to make decisions, being excluded from the data entails that one's interests, needs and preferences are not taken into consideration (Lerman, 2013). Big data's exclusions are often individuals from

disadvantaged groups who have insufficient access to technology. However new categories of individuals who are specifically disadvantaged by big data in education may emerge. For example, children who participate in competitive sports may spend less time online and as a result their electronic profile may be inaccurate and unfavorable. The extent to which these biases should trouble us, as a matter of educational justice, will depend primarily on how significantly they afflict those who suffer from them.

Biases in big data in education are especially troubling for several reasons. First, while it is fairly well known and empirically verified that human decision-making is affected by implicit bias, algorithms are generally perceived as scientific and neutral. Therefore, when relying on algorithms results in unequal outcomes, these outcomes are accepted as inevitable and justified.

Moreover, relying on algorithmic decision-making in education, as opposed to other domains, creates unique challenges, because the algorithms' predictions cannot be effectively verified ex-post. After identifying potential tax evaders, for example, an algorithm-based alert is validated by an actual audit, and false predictions can be detected and corrected. An innocent individual is surely inconvenienced by being targeted by the algorithm, but the harm is relatively contained (and reasonable, all things considered). Identifying false alarms also enables the algorithm to adjust and improve its predictions. Conversely, a prediction that leads to the assignment of a student to a certain track does more than indicate the student's ability: it constitutes it. Teachers unintentionally treat students according to what they perceive to be their ability, which in turn reinforces their perceptions. Categorizing students according to their ability also affects the curricula they are taught and the resources they are allocated, further influencing their abilities. It is extremely hard, therefore, to verify the algorithm's predictions and to expose its mistakes.

Scientists and algorithm designers have already begun addressing the challenge of discrimination in algorithms, experimenting with different possibilities such as removing discriminatory attributes and attributes that correlate with them (zip code, for example often strongly correlates race), or manipulating historical datasets to be more reflective of social composition (Calders and Žliobaitė, 2013). The challenge when incorporating these technological solutions is to maintain the predictive accuracy of the algorithm. Social

inequality, rather than implicit bias, is still the primary cause for educational inequality, and algorithms simply mirror that inequality. Scientists should target the implicit biases that affect decision-making, and not educational inequality as a whole. The greater challenge, of promoting educational equality, is likely to continue burdening educators and scholars in the future.

Conclusion

Like many other educational reforms, the technological revolution is likely to have significant effects in terms of educational justice. The paper discussed four issues that are likely to be affected by the incorporation of ICT in education, and a complex picture of the expected benefits and challenges of big data emerge. It seems, on the one hand, that despite these extremely significant changes in the way education will be provided and organized, the traditional challenges that have occupied educators and scholars will continue to trouble us. On the other hand, some of the issues discussed above may undergo a more fundamental change.

Thus, the problem of scarce resources will persist, although perhaps the need will shift to other resources. Biases will still pervade decision-making, afflicting both the groups that are traditionally disadvantaged, and possibly also others. And while it is unclear, as of yet, whether big data will exacerbate these injustices or not, and the answers will unravel as experience accumulates, the fundamental challenge remains the same.

Education's positional good, and the peer effects associated with education are two issues in which the change that ICT brings runs deeper, and may require rethinking some of the basic tenets that underlie our theories of educational justice. Thus, if indeed big data de-positionalizes K-12 education, this extremely salient factor will be removed from the educational justice debate with significant ramifications for principles of educational equality. Similarly, if peer effects are eliminated, or significantly decreased, one of the primary justifications for educational integration will cease to be valid.

The effects of ICT on educational justice, then, are yet to be seen. It is already clear, though, that the technological revolution in education will create new challenges in terms of distributive justice that will demand the attention of educators, policy makers and philosophers. In order to meet these challenges philosophers must make an effort to gain

a better understanding of educational technologies, and to incorporate this knowledge into discussions of educational justice. This paper aims to contribute to this effort and thus to ensure that educational justice theory does not lose its practical relevance in an era of big data.

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[1] Big data is not easily defined, but in general refers to "large and complex datasets collected from digital and conventional sources that are not easily managed by traditional applications or processes." (Reyes, 2015: 75).

[2] Although scarcity is also related to education's positional character, and in that sense remains even when objective scarcity disappears. This will be discussed later on in the paper.

[3] Although one study shows that employers tended to evaluate candidates that participated in MOOCs favorably, viewing participation as indicative of attributes like motivation and a desire to learn (Walton-Bratford et al, 2014).

[4] This section is based on previous work by the author and co-author Yoni Har Carmel (forthcoming).

[5] http://evaas.sas.com.

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