Artificial intelligence and the mobilities of inclusion

Citation for published version:
Gallagher, M 2019, Artificial intelligence and the mobilities of inclusion: The accumulated advantages of 5G networks and surfacing outliers. in J Knox, Y Wang & M Gallagher (eds), *Artificial Intelligence and Inclusive Education: Speculative Futures and Emerging Practices.* Perspectives on Rethinking and Reforming Education, Springer, Cham, pp. 179-194. https://doi.org/10.1007/978-981-13-8161-4_11

Digital Object Identifier (DOI):
10.1007/978-981-13-8161-4_11

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
Artificial Intelligence and Inclusive Education

Artificial intelligence and the mobilities of inclusion: the accumulated advantages of 5G networks, machine learning, and surfacing outliers

Author
Dr Michael Gallagher
Centre for Research in Digital Education
Moray House School of Education, University of Edinburgh
michael.s.gallagher@ed.ac.uk

Dr Michael Gallagher is a member of the Centre for Research in Digital Education at the University of Edinburgh and Director of Panoply Digital, a consultancy dedicated to mobile for development (M4D). His research focus is the mobilities and immobilities exhibited by groups in flux and how technology is used to manage these mobilities. He employs a theoretical lens from mobilities frameworks to unpick the actors in these larger mobilities systems, or "the distribution of agency between people, places, and material assemblages of connectivity" (Sheller, 2017). Methodologically, he tends towards ethnographies, or lived accounts of practice, and with a particular emphasis on the material realities of such ethnographies, An emphasis on mobilities theory provides opportunity for methods that are speculative, "linked to arts, design, and public policy" (Sheller 2017).

Keywords
Artificial intelligence, curriculum, accumulated advantage, ICT4D, digital divide, mobile learning

Abstract

The burgeoning use of artificial intelligence in a learning increasingly mediated through mobile technology makes inclusion problematic. This is largely due to the sheer ubiquity of mobile technology globally, the complexity of the machine learning regimens needed to function within increasingly sophisticated 5G cellular networks, and the legions of professionals needed to initiate and maintain these AI and mobile ecosystems. The promise of artificial intelligence in inclusion is curtailed precisely due to the accumulated advantage (the Matthew effect) presented in such a technological sophistication: only those with the most sophisticated and agile of educational systems will stand to benefit, a scenario that poses significant impact on inclusion strategies increasingly mediated through ICT.

Further, the accumulated advantage is not only a dichotomy between those with access to these sophisticated technologies and those that do not enjoy that same privilege. A further parallel is between the "curriculum" of machine learning of artificial intelligence in 5G networks as outlined in Li et al (2017) and traditional and human-centred educational curricula that is being increasingly redrawn as a reductionist enterprise aligned with national and international quantitative metrics. While AI has evolved to include multidisciplinary techniques such as machine learning, optimization theory, game theory, control theory, and meta-heuristics in both supervised and unsupervised formats, traditional educational curricula is increasingly influenced by third party commercial enterprises and reductionist moves towards computational thinking.

This poses significant disadvantage to educational inclusion beyond technological advantage, the sophistication of machine learning curricula, or the general paucity of human curricula increasingly modeled on computational thinking; the biases at work in larger society are encoded into the datasets that machine learning operates. Inclusion operates, statistically, as an outlier in these data-driven environments; as an equitable model in education, largely designed to *counter* prevailing societal biases, rather than *conform* to them. The equity that this inclusion seeks to provide is not inherently a naturally-occurring entity and will not render naturally in the data that AI is learning

from. As more and more education is engaged through mobile technology and more and more of that mobile education is driven by an artificial intelligence emerging from curricula of greater and greater sophistication, a situation emerges that poses great challenges for any sort of meaningful inclusion, particularly in the potential acceleration of entrenched advantage.

Relationality and mobility: Positioning AI in a broader sociocultural context

The futures of artificial intelligence and mobile technology are inexorably linked precisely due to the amounts of data generated by the latter being used to fuel the machine learning of the former. Mobile web traffic has overtaken desktop and laptop-based in many if not most markets with mobile data expected to increase tenfold between 2016-2022 growing at a rate of 45% in that span annually (Ericsson 2018); and the number of unique mobile subscribers will reach 5.9 billion by 2025, equivalent to 71% of the world's population (GSMA 2018a). The big data required for machine learning to build intelligent models suggests a natural pivot to mobile technology; if the future of artificial intelligence needs increasingly more user data to build its intelligence, it must engage in mobile, precisely because data is increasingly generated this way and particularly in developing contexts. This increase in mobile data has profound implications for education and inclusion.

Indeed, the burgeoning use of artificial intelligence in a learning increasingly mediated through mobile technology makes technological inclusion problematic. This is largely due to the sheer ubiquity of mobile technology globally, the complexity of the machine learning regimens needed to function within increasingly sophisticated 5G cellular networks, and the legions of professionals needed to initiate and maintain these AI and mobile ecosystems. The promise of artificial intelligence in education is curtailed precisely due to the accumulated advantage presented in such a technological sophistication: only those with the most sophisticated and agile of educational systems will stand to benefit, a scenario that poses significant impact on inclusion strategies increasingly mediated through ICT. The mobile context for the data that powers AI and the technological space in which much AI is deployed (via mobile technology) inherently involves issues of inclusion and exclusion at its onset. There are inherent differentiations of these issues surrounding technological access and use according to geographical, social, political, and economic. A failure to meaningfully address these differentiations will likely entrench existing relations of inclusions and exclusion.

Mobilities and Education

Yet the critique of such a system of accumulated advantage, and its potential impact on inclusion in education, requires a theoretical a lens which mobility theory graciously provides. Mobilities theory is typified by a structural typology consisting of five mobility types: mobility of objects, corporeal mobility, imaginative mobility, virtual mobility and communicative mobility (Fortunati and Taipale 2017). What this chapter is primarily concerned with is virtual mobility, the mobility experienced online by internet users; communicative mobility, person-to-person communication modalities connected to movement; and the effects of these on imaginative mobilities, the representation of mobility as elaborated and broadcasted by the media (2017). It is in the intersection of these three mobilities that the use of artificial intelligence in education has the greatest potential impact.

More importantly, mobilities theory is largely non-representational and concerned with the relationality of "bodies and objects and conjoined metabolisms of bodies and space, so that the pulses and rhythms between them are discernible in the shifting mobilities of urban life" (Lefebvre 2004). While this chapter is not concerned with the urban of this description, it is concerned with the relationality of the movements of educational systems, AI, and people; as such mobilities theory presents utility in understanding the "dynamic intersections of people, objects and places, interfaces of the social and spatial" (Waterton and Watson 2013) that permeate this discussion of AI and inclusion.

The use of mobilities theory, beyond providing utilitarian value in unpacking the intersectionality that AI in education foregrounds, also inherently broadens the theoretical gaze away from a humanist assumption, emphasising the material relations that exist between humans and non-humans (Fenwick et al 2011), the mobilities that course through these relations, and the new educational spaces created as a result.

Traditional educational systems built from a territoriality emerging from the compulsory schooling legislation of many countries in the 19th and 20th centuries engendered a particular expectation of social mobility. AI supplants aspects of this educational mobility with potentially dramatic consequences. A focus on mobility pushes away from territoriality with a host of attendant and both positive and desultory effects. These effects seep into educational systems as we are taken away "from such a focus on bounded regions and terrains (the nation, the city, the campus), toward a consideration of the new kinds of 'mobilities and moorings' (Hannam et al. 2006: 2) experienced in contemporary political, economic and social space" (Bayne et al., 2014). AI supplants actors in relational educational systems, reconfiguring both the mobilities made possible in this new educational space, and introducing "extensive systems of immobility" (Sheller & Urry, 2006, 210) in its wake.

Using this mobilities lens with artificial intelligence is necessary precisely because of the significance of the departure that AI poses for traditional educational systems, and consequently the potentially radical redrawing of the spaces of education created as a result. Emergent technologies such as AI 'introduce a significant break in the way individuals, groups and society as a whole conduct their everyday activities, as well as add new dimensions to our understanding of the social world'; these shifts have cascading "practical and epistemological implications for mobile methods" (Hesse-Biber 2011: 4). The immobilities posed by this new relationality are both offshoots of the "material inequalities in the distribution of communication technologies" (Chouliaraki 2012), discussed further in this chapter as an ownership and access inequality, and technological intent; beyond human ownership and access of ICT, AI largely assumes no human involvement at all. This poses a scenario ripe for accumulated advantage: those with significant access to ICT and sophisticated educational systems stand to accumulate advantage by this new relationality. This is positioned in the following sections through a discussion of the Matthew effect and its codification of immobility.

Matthew effect as a means of investigating mobilities: education, access, hardware, code, and AI as boundary objects

The Matthew effect, or the Matthew effect of accumulated advantage was originally designed to refer to the social processes through which various kinds of opportunities for scientific inquiry as well as the subsequent symbolic and material rewards for the results of that inquiry tend to accumulate" (Merton, 1988) in certain practitioners or organisations of science. Namely that those scientists or scientific organisations that have invested in their own development and have gleaned some success from those initial investments will accumulate advantage over a course of time. Broadly, the Matthew effect is used to describe "the general pattern of self-reinforcing inequality" that can be related to economic wealth, political power, influence, educational attainment, or any other desired commodity (Perc, 2014). The gaps between those who accumulated advantage (the haves) and those without (the have-nots) "widen until dampened by countervailing processes" (Merton 1988), such as legislation, educational interventions, or shifts in public sentiment or social mores.

The Matthew effect also contributes to a number of other concepts in the social sciences, education included, that may be broadly characterized as social spirals. These spirals exemplify positive feedback loops, in which processes feed upon themselves in such a way as to cause nonlinear patterns of growth (Perc 2014). The manifestation of the Matthew effect in education is well documented. Stanovich has documented this effect through the impact of early age reading on the learning of new skills subsequently, noting that falling behind in reading accumulates a disadvantage that proves notably difficult to overcome in later life (2008). Raizada & Kishiyama (2010) further this Matthew effect in education by demonstrating the impact of socioeconomic status on brain development and in enabling a lifelong self-reinforcing trend towards self-control and greater intellectual discovery. As we investigate the speculative futures of artificial intelligence in education towards inclusion, it is critical to consider these feedback loops being created in this educational system, and how they represent potentially an exponential acceleration of accumulated advantage.

The Matthew effect provides utility to a mobilities interpretation of the use of AI in education by identifying the material of those mobilities and how that material is increasingly situated in a select few. Further, it assists in identifying the boundary objects of these mobilities, Boundary objects are "artifacts, documents, terms, concepts, and other forms of reification around which communities of practice can organize their interconnections" (Wenger 1998). Positioning AI itself as a boundary object both provides analytical utility (Star 1998) and remains true to this original position of boundary objects, despite the lessening of agency suggested in its use. With AI, boundary objects function as material by which a community can organise their interconnections; with AI, the shift from possibility (*can organise*) to requirement *(is organised by*) is implied. Star (1998) advanced boundary objects as a data structure for artificial intelligence as they are designed to be adaptable across multiple viewpoints yet maintain some continuity of identity.

Examples of how this Matthew effect is codified through boundary objects are numerous; Merton details the use of intellectual property restrictions as a means of consolidating accumulated advantage for scientists (1988), Bothner et al (2010) position the accumulation of junior colleagues in academia in much the same way. Merton (1968) discusses admission to the French Academy and its artificial limitation of seats (40) as a means of consolidating advantage and status; Yang et al (2015) finds evidence of the Matthew effect in the uneven distribution of academicians of the Chinese Academy of Sciences among different regions and disciplines. Antonelli and Crespi (2013) discussed business in the context of discretionary allocation of public R&D subsidies.

Largely what these measures of consolidation collectively represent is a means of manipulating mobility: "the aspiring crowd is likely to exhibit particular structural features (beyond large size) and associated behaviors that make it harder to cross the status boundary and enter the elite status grade—whether that grade is an honorific group of scientists or a band of corporate officers" (Piezunka et al 2017). These measures of consolidation exist as opaque and largely inaccessible boundary objects, performing a bridging function to the larger community even if the individual engaging with them is not. Boundary objects allow different groups to work together without consensus (Star 2010) and inform those without advantage as to the contours of the community where the accumulated advantage continues to manifest itself (much as is the case with the French Academy example and the prestige afforded those with a seat). AI functions in much this same way: it allows potentially for greater sophistication in collaborative structure for those *within*, and reveals the boundaries of the community to those *without* community access. Access to and use of AI signals further advantage in community membership.

The Matthew effect extends to the internet itself and the technology used to access it and indeed these technologies can and should be seen as boundary objects as they are used by communities to organise their interconnections and mobilities within these interconnections. As AI is built from these earlier technological infrastructures of desktop and mobile connectivity, and indeed still is largely dependent on them, their role as a boundary object remains critical to any speculative future of education. Taipale (2016) discusses this in the context of internet access, noting the advantages of a mixed fixed/mobile internet connection in stimulating an advantageous, and accumulated, mobility conferred in the Finnish context on a largely young, male, and urban population.

The accumulated disadvantage of a lack of technological ownership and consistent use is felt disproportionately by certain segments of the larger global population, primarily women, children, and broadly those from the Global South: Africa, which has mobile penetration of 82% and internet penetration of only 34%; Asia-Pacific with mobile penetration at near 100% and internet penetration at 48% (We Are Social, 2018). Globally, women are 12% less likely than men to use the internet (ITU 2017). Barriers to internet access and use include cost of devices and data, lack of awareness and understanding of the internet, lack of education, low confidence, lack of digital skills, poor literacy, a feeling that the internet is not relevant, concerns around safety and security and lack of access to infrastructure, such as quality network coverage and electricity, all of which are experienced more acutely than men (GSMA 2018b). Computer home ownership is rare throughout most of the world; broadband connectivity even less so. All of these limitations mitigate the capacities of these disadvantaged groups to organise their interconnections at a scale and an efficiency enjoyed by those without these limitations; as such, the technology itself functions as a boundary object. For most of the world, mobile technology is and will remain the ICT of first, and in some cases only, use, yet differentiated access within that mobile technological environment exacerbates and even accelerates the Matthew effect.

Yet this is not merely a technological access and use issue. Mobile technology carries with it significant capacity to shape sociocultural exchanges, as well as acting as the "material symbol of one's relational ties" (Gergen 2003). It acts as a social object (Srivastava 2005) rather than merely as a technological one and is associated with social relationships both symbolically and functionally; further, it provides capacity for and structures the intimacy of these social relationships (Goggin 2012). As such, the Matthew effect as it applies to mobile technology is not merely the expression of a financial, educational, technological or political deficit, but rather a sociocultural one: the lack of mobile technology, or the possession of a less advanced mobile technology, or the accompanying access issues that governs its use (cellular coverage, cost, literacy or educational capacity, gender dynamics, and more) mitigates the possibility of managing networks of social relationships optimally. The social self in this position enjoys less advantage, and a relative position within a larger sociocultural power dynamic suffers as a result. The performance of sociality within the conduit of mobile technology consequently differentiates dramatically: "the types of mobile phones, usage, and text messages can become key tools in practices of display and disguise, two strategies underpinning the performance of respect" (Pype 2018), tools that provide capacity for increasingly nuanced communication at greater price points.

If we are to extend this sociocultural lens in mobile technology to the use of artificial intelligence, we see significant limitations in the types of data being generated that can feed into machine learning; indeed if data is being generated at all (technological inclusion is particularly pronounced in certain regions-South Asia and sub-Saharan Africa, e.g.- and amongst particular groups-the gender digital divide, in particular) it is limited to particular frames of activity and is limited, often, to particular actors within communities. Sinha (2018) and others have pointed to the risks that artificial intelligence poses for labour participation for women, but these risks extend beyond financial inclusion. The paucity of meaningful data available for machine learning for particular groups in particular regions will likely reinforce existing sociocultural barriers to inclusion by rendering particular social practices invisible. The accompanying management of social relationships through AI presents significant advantage- personalisation, recommendation services, and the general data-driven automation of one's social position- yet the disadvantages are rendered largely invisible existing as they exist largely outside technological data.

In the frame of artificial intelligence and inclusion, the Matthew effect as expressed in mobile technology is particularly problematic precisely due to the intimacy of the technology and its relationship and structuring of the social engagements encapsulated therein. This includes the use of mobile technology in education and the articulation of the artificial intelligence used within this mobile technology. Those with greater technological capacity (emerging from financial and educational advantages) carry with them the possibility of greater capacity for making use of AI educationally: as a key tool in the performance of social relations for educational effect, in the organisation of interconnections and mobilities within these interconnections for educational communities, and even in the offloading of educational labour onto AI (in the execution of computational educational activities, the completion of administrative duties, in educational timetabling and more). Due to its sheer ubiquity and the social intimacy that it structures, mobile technology represents the most seamless bridge between human education and artificial intelligence.

5G Networks and Complexity and Cost as Barriers to Entry

Yet this bridge is increasingly laden with barriers that mitigate inclusion. The increasing use of artificial intelligence more broadly further illustrates the point, precisely in the types of operating infrastructures it requires to prove beneficial. In the space of mobile technology, this is largely the purview of 5G networks. 5G networks are illustrative of the intersectionality of accumulated advantage and the myriad of ways in which this might express itself educationally. 5G cellular networks have built within them access and service provisioning mechanisms unavailable to past mobile networks, mechanisms that both increase the potential complexity of mobile networks and the scope of the benefits provided therein.

5G networks are also inexorably linked to the future of artificial intelligence for both machine learning content (user data, primarily) and the precision required in the execution of AI applications. Some AI applications, such as ones with augmented and virtual realities (AR/VR), require extremely high connection speeds; 5G networks offer multi-gigabit connections. Many other AI applications such as drone surveillance might would require large amounts of data capacity and 5G brings this capacity. AI applications will likely require low latency and 5G offers sub-millisecond latency, which is more than 10 times quicker than 4G (Sangam 2018). Pragmatically, this potentially involves machine learning with unstructured data-a mixture of audio, video, text and numbers that humans process routinely-towards the execution of particular tasks: personal assistants distinguishing commands from different voices in a household; AI stitching together 3D composites of images taken by drones and mobile phones of an emergency response site, to name but two examples.

Technologically, the configurable parameters of 2G nodes were 500, 1000 in 3G networks, 1500 in 4G networks with 5G networks expected to surpass 2000 (Li et al 2017). The sheer volume of configurations made possible with an ever-increasing range of parameters of nodes, along with the self-organising features of a 5G network (self-configuration, self-optimization, and self-healing), present a complexity that many without sufficient resources will not be able to enjoy. 5G networks adjust the bandwidth of the data transmission to the variable user density and the speed of their movements, yet due to the limited storage and processing capacity of the mobile devices themselves (as opposed to the 5G mobile network as a whole), the processing and storage of internet queries and activities takes place in cloud computing systems (Khetselius et al 2017), thereby adding an additional layer of complexity (exchanges between the device, the internet, and the cloud storage and processing centers) and cost (bandwidth, cloud storage, and more).

Artificial intelligence would 'live' in the complexity of this cloud architecture, providing measures of intelligent automation, predictive analytics, and proactive interventions, ultimately moving towards autonomous systems that "understand, learn, predict, adopt and operate autonomously and give rise to a spectrum of intelligent implementation" (Khetselius et al 2017). The sheer complexity of such a system and the possibility, if not probability, of autonomous systems operating within it present considerable challenges to those operating on the deficit end of the Matthew effect.

The economic barriers to entry to 5G networks are sufficient in and of themselves to prohibit mobility through them. The rollout of 5G networks in Europe alone is expected to account for €57 billion by 2020. This prohibitive cost of entry is merely the first of two time markers on a larger Matthew effect; the potential benefits (estimated in the EU at €113 billion by 2025) are thereby lost by this barrier to entry to the 5G environment (Mansell 2017), benefits that are likely funneled into further research and development. Further are political considerations as the benefits of investments in 5G networks require concerted and elongated effort, likely across several political regimes; advantages exist in regional cohesion to offset costs and increase the saturation in 5G networks. The 5G Infrastructure Public Private Partnership (5G PPP 2014) is an example of just such a coordinated regional response: 5G PPP is a joint initiative between the European Commission and European ICT industry (ICT manufacturers, telecommunications operators, service providers, SMEs and researcher Institutions) to research and accelerate the adoption of a 5G infrastructure. Such a coordinated, interdisciplinary and regional response is unavailable to many.

It is likely that in some sectors, the advent of 5G mobile networks will exacerbate the digital divide, despite technological innovations such as free-space optical links and solar-powered equipment in offsetting the cost and skills needed to deploy 5G networks (Lavery et al 2018). The "material inequalities in the distribution of communication technologies" (Chouliaraki 2012) is a highly intersectional enterprise with potential immobilities presented at each layer of the intersection. It is through this intersectional 5G enterprise that much of the world will interact with or be interacted on by artificial intelligence and will do so in increasingly reduced timeframes: "it took less than 30 years to successfully transform cellular networks from pure telephony systems to networks that can transport rich multimedia content and have a profound impact on our daily life." (Liu 2018) and presumably less time for the same to happen with the AI that will increasingly impact our lives through 5G networks.

The Emerging Divide: AI and Educational Curricula

Yet the digital divide and its spillover effects on inclusion is never exclusively a digital enterprise; as many have posited, it extends well beyond mere technological ownership and extends well into the values and outcomes encoded into education and associated curricula. What the digital suggests in this instance, particularly in the use of artificial intelligence across mobile networks, is both the sheer ubiquity of such an enterprise (in respect to mobile ownership rates worldwide) and the acceleration of deficits generated in such ubiquity: the intersection of AI, 5G networks, and a supporting educational infrastructure to supply expertise to such an endeavor is available to a very select few.

This very select few has entrenched this accumulated advantage presented by AI and its use in 5G networks by a structuring of the underlying data on which AI depends. The US, the European Union, and China are aligning policy with other intersectional factors, such as education, infrastructure, and more, to develop data-based economies of scale and in doing so have created three distinct data realms with different approaches to data governance (Aaronson and Leblond 2018). These data realms act as accelerants to the digital divide: those without the means for scale and differentiation (to act independently as a data regime) must spend resources in compliance towards these three regimes.

These data regimes, along with the current negative uses of data that have the potential to accelerate with AI (surveillance, reinforcement of monopolies, loss of privacy, and algorithmic profiling, all of which are likely to disproportionately affect those without means), present a data injustice (Heeks and Renken 2018) in that there is a lack of fairness in the way people are made visible, represented, and treated as a result of their production of digital data (Taylor 2017). Artificial intelligence has the capacity to accelerate these injustices by (further) abstracting the relationship between private power and public accountability (Joh 2018). As AI emerged largely from the private sector and mobilises through largely private 5G networks operating on slices of the auctioned mobile spectrum, public accountability becomes a convoluted intersectional affair. The potential for injustice and the increase of the digital divide is probable.

All of this carries with it profound challenges to existing educational systems and measures taken to improve inclusion; indeed these challenges are encoded in them. Accumulated advantage is not only a dichotomy between those with access to these sophisticated technologies and those that do not enjoy that same privilege. A further parallel is between the "curriculum" of artificial intelligence for learning in 5G networks as outlined in Li et al (2017) and traditional and human-centred educational curricula that is being increasingly redrawn as a reductionist enterprise aligned with national and international quantitative metrics. AI has evolved to include multidisciplinary techniques such as machine learning, optimization theory, game theory, control theory, and meta-heuristics, and various pedagogical applications of these theories in machine learning, unsupervised learning, and reinforcement learning (2017).

Unsupervised machine learning, in particular, bears resemblance to adaptive learning and self-efficacy learning programmes in humans. Unsupervised machine learning exists as a measure of learning consolidation, relying on the AI itself to find the embedded patterns in its own input, rather than through the direction of a secondary instructional agent (2017). It exists as a measure of formative assessment whereby the learner (ie, the AI) identifies hidden patterns in its input and identifies strategies for consolidating these patterns in future activities. Rather than using AI as a channel for formative assessment for human students in a host of potential instructional roles such as peers, team members, game players, coworkers, teachers (Graesser and McDaniel 2017) and through ongoing "stealth" assessment strategies-a game-based assessment framework which links observed behavior with evolving competencies (Min et al 2017), AI uses unsupervised learning as formative assessment for itself. "In the field of AI, unsupervised learning is applied to estimate the hidden layer parameters in neural networks and plays an important role in deep learning methods" and it is the most widely used AI category in mobile (cellular) networks (Li et al 2017). The AI that emerges from the curricula of 5G networks and winds into educational spaces will be one that has largely learnt from itself, without direct instruction from human agents. The impact of these techno-educational configurations and their development outside human environments on educational inclusion is potentially significant: curricula, pedagogy, assessments, evaluations, behavioral metrics, and an alignment of educational practice with linear (and predictable) activity.

Traditional educational curricula designed for humans is increasingly influenced by third party commercial enterprises designed to largely simplify the messiness of the educational experience. The commodification of learning, redrawn increasingly as a commercial enterprise, has impacted curriculum development, seeing it in the much the same way as policy development: "a linear succession of events (formulation, implementation, evaluation) rather than as a complex, messy and iterative process" (Whitty 2017). This shifting of education towards predictable evaluation and evidence-based policy paradigms, largely attempts to tidy the messiness, have increased private-sector participation in education largely through the use of technology (Riep 2017). This alignment of commercial and educational objectives, and its subsequent impact on educational curricula is born most heavily on those laboring under an accumulated disadvantage.

Education is largely being redrawn as a reductionist enterprise as curricula is being aligned to largely derivative computational models of learning (Azhar 2016). It is an education that is designed to provide skills associated with an unbundled labour market: task decomposition, task completion, moments of labour in small gaps in time (Teevan 2016), largely a predictable and granular approach to education. Education is increasingly attempting to recreate the computation practices at work in the technology sector and repurpose them into pedagogical employ (discussed in Gallagher 2019).

Examples abound. Bridge International Academies, particularly active and contentious in India, Uganda, Liberia, and Kenya, use technologies and a highly formalised curriculum "to construct mass markets for low-cost schooling, including GPS devices that map low-income communities, smartphones that automate administrative functions, and computer devices that perform the duties of a teacher" (Riep 2017). As Riep details, Bridge International Academies take this turn towards computational thinking towards a new power dynamic through the use of "teacher-computers", which are tablet e-readers that convey '… step-by-step instructions explaining what teachers should do and say during any given moment of a class' (BIA 2016); as of 2018, the significant emphasis on tablets as "teacher-computers" has been replaced with tablets as "teacher guides" (BIA 2018) yet the flow from computer to teacher to student remains, what Riep refers to as a type of techagogy, a technology-directed form of pedagogy in which instruction is led by machines. While increasingly contentious and in some instances ending its operations (in Uganda, detailed in McVeigh and Lyons, 2017), Bridge International Academies is merely representative of this drive towards techagogy; the political realignment of the teacher servicing the instructions of the computer is merely a further element of a larger intersectionality that potentially accelerates the Matthew effect.

The curriculum associated with the machine learning of artificial learning is suffering from no such reductionism: as discussed, machine learning, optimization theory, game theory, control theory, meta-heuristics, unsupervised learning, and reinforcement learning (Liu et al 2017) all are employed to develop AI in 5G networks. It is a curriculum growing in dynamic complexity to service an increasingly complex field; human-centred education in contrast is increasingly reduced to align with measures designed to increased predictable outcomes.

Ultimately, the question that can conceivably be asked in such a scenario is whether the curriculum of artificial intelligence in 5G networks pedagogically surpasses that of traditional educational curricula, particularly in regions where education is increasingly mediated through third party providers and computational curricula, such as initiatives like Bridge International Academies. As more and more education is engaged through a larger and increasingly commercial educational technology enterprise and more and more of that education is driven by an artificial intelligence emerging from curricula of greater and greater sophistication, a situation emerges that poses great challenges for educational inclusion, particularly for those that largely sit outside the advantageous intersections of education and technology.

Rethinking Equitable Futures of Inclusion

Returning to the potential acceleration of the Matthew effect in light of the technological sophistication inherent to artificial intelligence, 5G networks, and increasingly dynamic (for AI) and deterministic (for humans) educational curricula, we pause to consider offsets to this seemingly inevitable accumulation of advantage, what Piezunka et al (2017) refer to as external judges which seek to limit the operation of the Matthew effect. These external judges might include social unrest or outage (Bebchuk 2009), policy and legislation, ethical frameworks, and educational curricula, all of which have spillover effects on inclusion.

As the subject of this chapter is the use of AI in education for inclusion, what follows will cleave to this subject, but it bears mentioning that the weight of non-educational external judges (policy, legislation, data protection, possible outrage over surveillance, and transparency) will more greatly impact the shape of the the marriage of AI and inclusion than the curriculum used to engage it. However, a curricular focus is significant in that it is largely a codification of entrenched values and advantages (the curriculum as political barometer of what *is*) and an aspirational endeavor (as a measure of what it *could be*). As such, the use of AI in education requires potential offsets to the Matthew effect that will likely emerge as a result, particularly for those traditionally disadvantaged groups which inclusion has attempted to serve. These offsets are presented by Dignum (2017) as AI development principles:

> "Accountability: an AI system needs to to be able to justify its own decisions based on the algorithms and the data used by it. We have to equip AI systems with the moral values and societal norms that are used in the context in which these systems operate; Responsibility: although AI systems are autonomous, their decisions should be linked to all the stakeholders who contributed in developing them: manufacturers, developers, users and owners. All of them will be responsible for the system's behaviour; Transparency: users need to be able to inspect and verify the algorithms and data used by the system to make and implement decisions." (2017).

Educational institutions that seek to employ AI are further stakeholders in this process, beholden to the same measures of accountability, responsibility, and transparency that Dignum presents here, measures that are increasingly at odds with the data that AI learns from.

As with all data-driven technologies, the underlying data that the AI learns from is sensitive to discrimination and bias (Caliskan et al 2017), a point of particular concern for inclusion. Decisions emerging from AI are assumed, incorrectly, to be emerging from fair and unbiased computations and are less likely to be questioned as biased than those from human agents (The AI Now Report, 2016), a position that proves particularly problematic for educational organisations engaged in inclusion, ones that will largely lack the expertise to unpick the biases emerging from AI engaged in ongoing educational work. AI in these spaces will largely be emerging from commercial enterprises and will largely encode the biases and discrimination at work in these commercial spaces (Miller et al 2018). Data used to train AI for employ in educational inclusion efforts will likely be drawn from broader sectors of society than just educational inclusion programmes. Broader datasets will likely reinforce the biases emerging from society as a whole, including biases that largely disadvantages students in inclusion programmes, an "unequal opportunity virus" (2018) coursing through the larger AI apparatus of machines, learning, and educational work.

As with all data-driven technologies, the AI will learn from the mobile data that what counts is what is counted, and what has happened will structure what will happen, learning that runs counter to the ideas of equitable educational inclusion. This learning serves to potentially neglect underrepresented groups and reinforce the barriers that made them largely underrepresented in the first instance. It is conceivable that AI that equitably services those in inclusion programmes will need to learn from data and neural networks emerging from these inclusion programmes themselves. This data and these neural networks operate on a different data-driven reality where inclusion is a stated objective of the educational enterprise, and not a statistical outlier in a broader societal dataset. Fidelity to Dignam's (2017) measures of accountability, responsibility, and transparency begin here in the selection of data that drives the learning of AI; too broad a data scope disadvantages those that would otherwise function computationally as outliers, students in inclusion programmes included.

Transparency demands that much of this work is surfaced in both human educational curricula, as a critical data education; and in AI curricula, as both surfacing the biases in the data driving machine learning and the employ of an external judge to mitigate these biases, perhaps by way of coding for equitable outcomes or external review. These external judges need to be structural directives, embedded into the machine learning curricula itself, and not merely post-facto compliance mechanisms. The sheer accelerating volume of mobile generated data and the primacy of its use in machine learning for future artificial intelligence makes this transparency problematic, however. Whether this sort of transparency is a probable, or even possible, future for the use of AI in educational inclusion remains to be seen, yet the potential acceleration of the Matthew effect in this context is clear as is the increased interdependence of mobile technology and artificial intelligence.

References

5GPPP (2014). The 5G Infrastructure Public-Private Partnership. Available at: https://5g-ppp.eu/#

Aaronson, S. A., & Leblond, P. (2018). Another Digital Divide: The Rise of Data Realms and its Implications for the WTO. Journal of International Economic Law, 21(2), 245-272.

Antonelli, C., & Crespi, F. (2013). The "Matthew effect" in R&D public subsidies: The Italian evidence. Technological Forecasting and Social Change, 80(8), 1523–1534.

Azhar, A. (2016). Coding is not enough, we need smarter skills. Financial Times. https://www.ft.com/content/7babc12c-f662-11e5-96db-fc683b5e52db.

Bayne, S., Gallagher, M. S., & Lamb, J. (2014). Being 'at' university: the social topologies of distance students. Higher Education, 67(5), 569-583.

Bebchuk, L. A. (2009). Pay without performance: The unfulfilled promise of executive compensation. Cambridge, MA: Harvard University Press.

Bothner M. S., Haynes R., Lee W., Smith E. B. (2010). When do Matthew effects occur? Journal of Mathematical Sociology, 34, 80-114.

Bridge International Academies (2018). Teaching tools. Accessed 13 July 2018. http://www.bridgeinternationalacademies.com/academics/tools/.

Bridge International Academies (2016). "Model." Accessed 22 January 2016. http://www.bridgeinternationalacademies.com/approach/model/

Caliskan, A., Bryson, J.J., & Narayanan, A. (2017). Semantics derived automatically from language corpora contain human-like biases. Science, 356, 183–186.

Dignum, V. (2018). Designing AI for human values. ITU Journal 1(1). Available at: https://www.itu.int/en/journal/001/Pages/01.aspx.

Ericsson (2018). Future mobile data usage and traffic growth. Available at: https://www.ericsson.com/en/mobility-report/future-mobile-data-usage-and-traffic-growth.

Fenwick, T., Edwards, R., & Sawchuk, P. (2011). Emerging approaches to educational research: Tracing the sociomaterial. London: Routledge.

Fortunati, L., & Taipale, S. (2017). Mobilities and the network of personal technologies: Refining the understanding of mobility structure. Telematics and Informatics, 34(2), 560-568.

Fujitani, S. & Minemura, K. (2017). An Analysis of Expectations for Artificial Intelligence-supporting Software in Mobile Learning. In J. Dron & S. Mishra (Eds.), Proceedings of E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education (pp. 918-922). Vancouver, British Columbia, Canada: Association for the Advancement of Computing in Education (AACE). Retrieved March 30, 2018 from https://www.learntechlib.org/p/181274/.

Gallagher, M. (2019 Forthcoming). Moving beyond Microwork: Rebundling Digital Education and Reterritorialising Digital Labour. In Peters, M. A.; Jandrić, P.; & Means, A. J. (Eds.) Education and Technological Unemployment. Springer.

Gergen, K.J. (2003). Self and community in the new floating worlds. In K. Nyiri (Ed.), Mobile democracy: Essays on society, self, and politics, Vienna: Passagen Verlag.

Goggin, G. (2012). Cell phone culture: Mobile technology in everyday life. London: Routledge.

Graesser, A., & McDaniel, B. (2017). Conversational agents can provide formative assessment, constructive learning, and adaptive instruction. In The Future of Assessment (85-112). London: Routledge.

GSMA (2018a). The Mobile Economy 2018. Available at: https://www.gsma.com/mobileeconomy/wp-content/uploads/2018/02/The-Mobile-Economy-Global-2018.pdf.

GSMA (2018b). A toolkit for researching women's internet access and use. Available at: https://www.gsma.com/mobilefordevelopment/wp-content/uploads/2018/05/GSMA-Women-and-Internet-Research-Toolkit_WEB.pdf.

Hannam, K., Sheller, M., & Urry, J. (2006). Editorial: Mobilities, immobilities and moorings. Mobilities, 1(1), 1–22.

Heeks, R., & Renken, J. (2018). Data justice for development: What would it mean?. Information Development, 34(1), 90-102.

Hesse-Biber, S. N. (Ed.). (2011). The handbook of emergent technologies in social research. Oxford: Oxford University Press.

International Telecommunication Union (ITU) (2017). ICT Facts and Figures 2017. Available at: https://www.itu.int/en/ITU-D/Statistics/Documents/facts/ICTFactsFigures2017.pdf.

Joh, E. E. (2018). Artificial Intelligence and Policing: First Questions. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3168779.

Khetselius, O. Y., Glushkov, A. V., Buyadzhi, V. V., & Bunyakova, Y. Y. (2017). New Generalized Chaos-Dynamical and Neural Networks Approach to Nonlinear Modeling of the Chaotic Dynamical Systems. Photoelectronics, (26), 29-40.

Lavery, M. P., Abadi, M. M., Bauer, R., Brambilla, G., Cheng, L., Cox, M. A., ... & Marquardt, C. (2018). Tackling Africa's digital divide. Nature Photonics, 12(5), 249-252.

Lefebvre, H., 2004. Rythmanalaysis: space, time and everyday life. London: Continuum.

Li, R., Zhao, Z., Zhou, X., Ding, G., Chen, Y., Wang, Z., & Zhang, H. (2017). Intelligent 5G: When cellular networks meet artificial intelligence. IEEE Wireless Communications, 24(5), 175-183.

Mansell, R. (2017). Are we losing control?. Intermedia, 45(3), 4-7.

McVeigh, K. and Lyons, K. (2017, May 5). "'Beyond justification': teachers decry UK backing for private schools in Africa," The Guardian. https://www.theguardian.com/global-development/2017/may/05/beyond-justification-teachers-decry-uk-backing-private-schools-africa-bridge-international-academies-kenya-lawsuit.

Merton, R. (1988). The Matthew Effect in Science, II: Cumulative Advantage and the Symbolism of Intellectual Property. Isis, 79 (4) (Dec., 1988): 606-623.

Merton R. K. (1968). The Matthew effect in science. Science, 159, 56-63.

Miller, F. A., Katz, J. H., & Gans, R. (2018). The OD Imperative to Add Inclusion to the Algorithms of Artificial Intelligence. OD PRACTITIONER, 50(1).

Min, W., Frankosky, M. H., Mott, B. W., Wiebe, E. N., Boyer, K. E., & Lester, J. C. (2017, June). Inducing Stealth Assessors from Game Interaction Data. In International Conference on Artificial Intelligence in Education (pp. 212-223). Springer, Cham.

Perc, M. (2014). The Matthew effect in empirical data. Journal of The Royal Society Interface, 11(98), 20140378.

Piezunka, H., Lee, W., Haynes, R., & Bothner, M. S. (2017). The Matthew effect as an unjust competitive advantage: Implications for competition near status boundaries. Journal of Management Inquiry, 1056492617737712.

Pype, JK. (2018). Mobile Secrets. Youth, Intimacy, and the Politics of Pretense in Mozambique by Julie-Soleil Archambault (review). African Studies Review, 61(1): 275-277.

Raizada RD, Kishiyama MM. 2010 Effects of socioeconomic status on brain development, and how cognitive neuroscience may contribute to levelling the playing field. Front. Hum. Neuroscience. 4, 3.

Riep, C. B. (2017). Fixing contradictions of education commercialisation: Pearson plc and the construction of its efficacy brand. Critical Studies in Education, 1-19.

Riep, C. B. (2017). Making markets for low-cost schooling: the devices and investments behind Bridge International Academies. Globalisation, Societies and Education, 15(3), 352-366.

Riep, C., & Machacek, M. (2016). Schooling the poor profitably: The innovations and deprivations of Bridge International Academies in Uganda.

Sangam, P. (2018). Living On The Wireless Edge With AI And 5G. Available: https://www.forbes.com/sites/forbescommunicationscouncil/2018/09/06/living-on-the-wireless-edge-with-ai-and-5g/#71cc8de6b6b4.

Schmid, R. F., Bernard, R. M., Borokhovski, E., Tamim, R. M., Abrami, P. C., Surkes, M. A., ... & Woods, J. (2014). The effects of technology use in postsecondary education: A meta-analysis of classroom applications. Computers & Education, 72, 271-291.

Sheller, M., & Urry, J. (2016). Mobilizing the new mobilities paradigm. Applied Mobilities, 1(1), 10-25.

Sheller, M., & Urry, J. (2006). The new mobilities paradigm. Environment and Planning A, 38, 207–226.

Sinha, S. (2018). Gender Digital Divide in India: Impacting Women's Participation in the Labour Market. In *Reflecting on India's Development* (pp. 293-310). Springer, Singapore.

Srivastava, L. (2005). Mobile phones and the evolution of social behavior. Behavior & Information Technology, 24 (2005): 111-129

Stanovich KE. (2008). Matthew effects in reading: some consequences of individual differences in the acquisition of literacy. J. Educ. 189, 23–55.

Star, S.L. (2010). This is not a boundary object: Reflections on the origin of a concept. Science, Technology, & Human Values, 35(5), 601-617.

Star, S.L. (1998). The structure of ill-structured solutions: Boundary objects and heterogeneous distributed problem solving. In Distributed artificial intelligence (pp. 37-54).

Taipale, S. (2016). Do the mobile-rich get richer? Internet use, travelling and social differentiations in Finland. New Media & Society, 18(1), 44-61.

Taylor, L. (2017). What is data justice? The case for connecting digital rights and freedoms globally. Big Data & Society, 4(2), 2053951717736335.

The AI Now Report. (2016, September 22). The social and economic implications of artificial intelligence technologies in the near-term. AI Now (Summary of public symposium). Available at: https://artificialintelligencenow.com/media/documents/AINowSummaryReport_3_RpmwKHu.pdf

Waterton, E., & Watson, S. (2013). Framing theory: Towards a critical imagination in heritage studies. International Journal of Heritage Studies, 19(6), 546-561.

Wenger, E. (1998). Communities of Practice: Learning, Meaning, and Identity (Learning in Doing: Social, Cognitive and Computational Perspectives). Cambridge: Cambridge University Press.

Whitty, G. (2017). The Marketization of Teacher Education: Threat or Opportunity?. In A Companion to Research in Teacher Education (pp. 373-383). Springer, Singapore.

Yang, X., Gu, X., Wang, Y., Hu, G., & Tang, L. (2015). The Matthew effect in China's science: evidence from academicians of Chinese Academy of Sciences. Scientometrics, 102(3), 2089-2105.