Digital Predictions: Children's futures, opportunities and obstacles

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Early childhood is seen by many as the ideal time to shape, support and encourage the child in order to become fully emotionally, intellectually and socially competent adults in the future. Discussions about the degree that children can participate and have agency in these processes are ongoing (Livingstone & Third, 2017). However, what happens with these agentic capacities – of adults and children – when decisions are made based on big data analytics and predictive algorithms?

Predictive algorithms are enacted in the everyday in multiple ways: for example, autosuggested Google search terms; Amazon recommendations; Google map travel time forecasts, or more controversially in predictive (and pre-emptive) policing practices. Prediction entails forecasting possible outcomes based on modelling, pattern detection and recognition through the (supervised and/or unsupervised) analysis of large data sets using iterative machine learning algorithmic processes (McQuillan, 2016). These practices inform strategies, policies and planning.

Within the contemporary child's digital ecosystem/s, there are multiple and diverse predictive practices currently and potentially at play. In the health sector, for example, predictive machine learning algorithms anticipate the likelihood of genetically detectable disorders in IVF pre-implantation screening (Regalado, 2017) or a child's possibility of developing autism (Ananthaswamy, 2017); in the education sector, they are being applied to educational data to identify students at risk or those in need of particular types of targeted intervention (Smith, 2017; Clow, 2013), in the commercial sector they are used to nudge particular types of purchasing decisions or to prompt data disclosures.

This chapter explores a number of predictive practices in early childhood initiatives. In doing so, the paper raises questions about the broader ethical, and normative issues that become apparent for child-rearing practices, and the possibilities for child or parental current and future agency when predictive practices and risk aversion drive the choices that are made available, hidden or negated.

The child as a data re/source

Children are increasingly positioned as data (re)sources and embedded in what I describe elsewhere (Willson, 2019) as algorithmic ecosystems. These systems intermingle, assist and disrupt. They rely heavily on various surveillance, reporting and data capture practices of the child from conception (even preconception) onwards for a range of diverse reasons and diverse stakeholders. Data about and from children are captured in multiple ways: biometric data recorded directly from their bodies through wearables and through data-enabled 'equipment' such as mattresses or child car seats; behavioural data extracted through camera surveillance, sensors and child monitor devices, or the translation of observation about these behaviours inputted into data systems by parents, carers, health or educational professionals; collected from child play activities directly through internet connected toys or through their engagement with entertainment and educational apps on tablets or smartphones are just a few of the myriad of data collection opportunities (Mascheroni, 2018; Lupton &Williamson, 2017).

For example, there has been a noticeable increase in the use of digital technologies directly by young children (zero to eight years old). This uptake has been assisted by the introduction and ease of use of touchscreens and other devices such as internet connected toys (Holloway & Green, 2016). According to a 2013 EU report looking at the digital practices of children from zero to eight years old, at least 50% of Swedish three to four year old children use touchscreens; 25, 50 and 70 % of American three, five and seven year olds respectively are online daily; and, 93 % of three to nine year old South Korean children are online for an average of between eight and nine hours weekly (Holloway, Green & Livingstone, 2013). Whether engaging with entertainment or educational activities offered by commercial or education providers, and with variable privacy measures and critical data literacy levels amongst children and their parents, the data collection possibilities of these types of engagement are immense.

We have been measuring, evaluating, recording and predicting children's activities and outcomes for all of modernity at least so the intent of these activities is not new. These practices form part of the underlying logic of liberal governance that informs governmental responsibility and care for populations and the individual's responsibility and care for the self. Increasing commercial encroachment into the everyday through data capture is an imperative of contemporary, or surveillance capitalism (Zuboff, 2015). The capacities for complex computing, big data analytic capacities and algorithmic machine learning push these practices into all areas of a child's life in a way previously unimaginable or physically unachievable.

As data is increasingly gathered, combined and analysed across an expanding, diverse array of everyday life activities, and as techniques and technologies become increasingly able to capture and manipulate these data, they in turn are employed as a way of managing risk, of driving agendas and shaping environments often in ways that we are not aware. What might these capacities and decisions mean for understanding agency when choices might be offered (or not) based on opaque predictions taking place unbeknownst to parents or child? What decisions might be made based on these predictions and the classificatory and correlation work that underpins it, and how might this affect a child's possible futures?

Predictive modelling, analytics and action

By predictive practices, I am referring to the use of predominantly machine learning techniques using structured and unstructured data and algorithmic analysis to uncover noticeable patterns in behaviours, characteristics or relationships, to anticipate likely outcomes, to nudge behaviours and attitudes and to be able to take pre-emptive action or acts of intervention as a result. In predictive analytics, a variety of machine learning algorithms are employed depending upon the particular task, purpose, and types of data involved. As noted above, data can be drawn from and combined with almost anything: sleep patterns, movement, emotions, physiology, genetics, performance, sound…the list is endless. Different algorithm techniques can be combined into model ensembles (Burrell, 2016) and applied to innumerable data combinations to identify the likelihood of possible future outcomes; i.e. they aim to predict the likelihood of a particular event or occurrence taking place, to anticipate future scenarios or to encourage particular outcomes. Insurance companies, for example, use predictive calculations in their determination and assessment of likely risk in order to calculate premiums: house insurance premiums according to the suburb you live in, the type of building construction, what types of locks you use. These determinations are in turn built on broad analyses of instances where there has been an insurance claim in order to detect patterns and to calculate a risk score.

Predictive analytics use an actuarial form of surveillance whereby large data sets are scanned, rather than the interrogation of individual instances. As the capacity for data collection, storage, aggregation and manipulation is expanded, the possibilities for predictive analytics and the types of activities that these techniques can be applied are similarly expanded. In his discussion of predictive algorithms and their use to initiate pre-emptive action, Andrejevic notes,

> *Preemptive practices do not intervene at the level of subject formation, but at that of the population. They are actuarial in the sense that they assess overall patterns of risk to determine probabilities of the emergence of particular events over time and space. The more comprehensive the data profile, the higher the likelihood of unearthing a relevant or actionable pattern. (2017: 883)*

A relevant or actionable pattern for an algorithm is identified by recognising correlations amongst data sets. Note that the emphasis here is upon correlation – a seeming alignment or the co-appearance of particular types of activities such as, for example, the percentage of school absence rates and lower school achievement levels are used to suggest possible causation. While in some ways, school attendance and level of performance appears a self-evident correlation (surely if the child is not at school, they are missing out on learning activities that will hinder their overall achievement), it is a relatively blunt instrument if translated into a governance approach that directs action at the absence of the population rather than at other possible underlying contributors in individual circumstances. It can also lead to more serious or problematic correlation assumptions. The use of predictive analytics to seek patterns for identifying risk of child abuse in order to inform child welfare decisions (Willson, 2019) is an example where heavily surveilled populations – lower socio-economic families from particular ethnic or racial groups- may have higher correlation patterns with rates of abuse by default as a result of their level of surveillance; however, this does not mean that these particular social or ethnic groups are inherently more abusive or that abuses are not happening amongst other populations who are less heavily surveilled. The potential for predictive practices when applied to children and child-rearing to highlight or obscure particular characteristics of individual or groups of children intentionally but also unintentionally, therefore, warrants closer interrogation.

These predictions can have material consequences that can be advantageous or disadvantageous for the child, the family and their future pathways. As Cope and Kalantzis (2016: 13) note about predictive analytics in relation to education,

> *Just as predictive analytics can be used to raise one's insurance premium or increase one's chance of arrest, so they might be used to predetermine a child's place in a learning track or a teacher's employment prospects*

It is therefore also important to recognise that prediction does not happen in isolation as a simple process of input, analysis and output; it is the tying of algorithmic outputs of recognised patterns or the production of particular modelled scenarios with strategies and actions informed by particular discourses that generate outcomes.

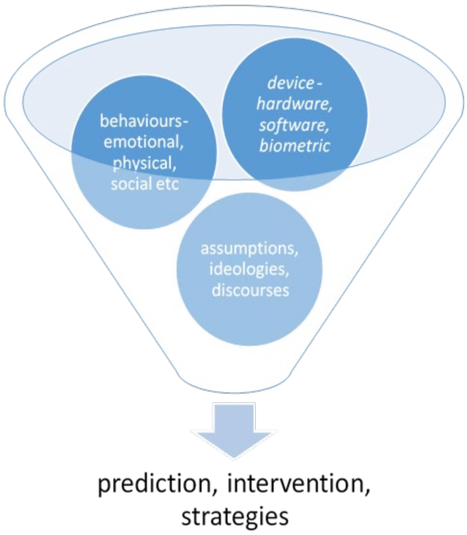

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Fig 1: Predictive assemblages

Such strategies or actions can be pre-emptive (in order to avert or capture an event), persuasive (to change or disrupt a predicted likely outcome) and targeted to specific individual characteristics or events. The use of predictive analytics in educational spaces can be used to identify children at risk of underperforming, overperforming or variously performing based on correlated patterns. The use of predictive analytics in health care can be used to identify possible markers in children for future diseases, or to manipulate genetic outcomes (Ananthaswamy, 2017; Regalado, 2017).

The perceived ability to anticipate and shape the future is alluring particularly in relation to children who are often positioned as vulnerable and malleable subjects. Indeed, it could be suggested there is a strong moral, social and cultural imperative that calls on society to do so. Commercial imaginaries are quick to harness this imperative in the types of services and offerings that are developed. Parents, educators and health professionals are all motivated to adopt technological tools and practices that will produce optimal child-rearing outcomes.

Writing about the data analytics industry, Beer (2019: 32) notes how the industry positions themselves in the marketplace:

> *Data and their analyses are presented as being a powerful, ongoing and permanent presence, giving constant insights that are always there. …. These analytics reveal hidden value in the data, they shine a light on organisations and show things that were previously invisible. They enable the future to be seen and an imagined future to be part of the present decisions that are taken. They see everything, in detail; nothing escapes their sight.*

The willingness to embrace initiatives that anticipate and shape the environment, abilities and practices of a child's future is revealed in the discussion below. Examples drawn from the education and commercial sectors reveal the range of activities upon which predictive attention is directed but also point to an increasing capacity for cross data aggregation between commercial entities, and also data collection, aggregation and analysis on the basis of data drawn from across the commercial and state sectors.

Commercial Care

In the commercial sector, products abound to allay the fears and concerns of parents. Tama Leaver (2017) has talked about the owlet: a sock the infant wears that measures oxygen intake, but there are a multitude of devices and wearables produced by private companies that capture infant behavioural and biological data, and offer benchmarking and advice in response to predicted outcomes. These devices not only capture the data for each individual child, the data can be manipulated, merged and used in other environments and in relation to other behavioural anticipation and device developments.

In order to be able to undertake relatively accurate predictive tasks, large amounts of data need to be collected and classified for that data to be able to be parsed and manipulated and 'made sense' of. Scale is important. Enough data needs to be gathered to render the outcomes generalisable and to increase accuracy in forecasting outcomes. Commercial applications and products alone may have the capacity to garner large swathes of data for such purposes, however, when linked or aggregated to data from other types of products the possibilities for predictive calculations are amplified.

Nod™, a digital 'sleep coach' developed by Rest Devices, Inc. and Johnson and Johnson, is marketed as a tool to help sleep deprived parents of infants manage their offspring's sleeping patterns. According to a blog post by one of the co-founders of Mimo, Dulcie Madden,

> *we realised we could deliver a personalized, self-learning sleep coach to parents, all via an app. Using huge amounts of sleep data, behavioral science, machine learning, clinical expertise, and love, we figured out that we could help identify a baby's sleep patterns, his or her parent's parenting style, key problems the family was facing, and then deliver a customized program for that family to do, night by night, to get more sleep within weeks.*
> *(https://www.mimobaby.com/single-post/2017/10/04/Solving-for-sleep)*

In fact, the Nod™ website promoting the app claims that 'within 30 days of using Nod, families experience 2 more hours of sleep a night, 2 hours fewer night wakings and 4 more hours added to longest overnight sleep period." (https://www.nodtosleep.com/). Nod™ is marketed as not only a way to manage a child's individual sleep patterns but also to be able to do this within the parameters of your parenting 'preferences'.

This has been made possible by the use of data analytics and machine learning and predictive modelling drawing from large data sets. According to a press release in 2017, "Both companies [Rest Devices, Inc and Johnson and Johnson] have studied hundreds of thousands of baby sleep patterns, so by combining their expertise, the Nod™ app can provide parents with an advanced, personalized sleep coaching system—like having a baby sleep expert in your own home." (https://www.jnj.com/innovation/nod-digital-baby-sleep-coach). These hundreds of thousands sleep pattern data have been captured through the Johnson's baby sleep app and through infant wearables and crib monitors sold by Rest Devices' Mimo products and presumably are used to train the underlying machine algorithms. Johnson also has the capacity to aggregate data across a range of operations and contexts

- Johnson and Johnson Pacific Limited encompass consumer health, medical device, pharmaceutical and biologics companies as part of their holdings.

Recommendations generated by Nod™ include advice on parenting practices and intervention strategies to change infant sleep patterns towards sleeping for longer with fewer interruptions: the ideal for sleep-deprived parents. Recommendations then are premised upon predicting possible outcomes based on past practices (those of the thousands of infants' sleep data that the algorithms have been trained on alongside the individual data that is captured for that particular child) in combination with data entered by sleep experts (https://www.babysleep.com/).

So, why are these types of activities worthy of consideration? Sidestepping concerns around privacy or questions about potential commercial nudging of consumers; there is a broader question about the delegation of parental consideration and judgement on the basis of abstracted data sets, and machine learning prediction.

In her discussion of a group of new mothers' use of parenting apps, Thornham (2019) notes a number of things relevant to our discussion here. First, she draws a link between the type of data these apps record and how they align with the questions these mothers are being asked for by their health professionals (p.176). This, she suggests, explains why the apps are so popular. Second, she then points to how these intermeshed relationships between data and feedback from the app are used as a way to alleviate anxiety and concern about parental approaches and infant progress while simultaneously aggravating this uncertainty through its very visibility via the prompted need to monitor and enter the requested data. As a result, not only did mothers use the information fed back to them via the app as a way to validate their experiences and performance, the health professionals and the mothers referred to this data rather than on the mothers' recollections as being more accurate and truthful (p. 177). A 'handing over' or delegation of maternal judgement, and agency in relation to infant care from mother to an app is undertaken creating a complicated relationship between infant, mother, technological device, the data obtained and interpreted and the health care professional. Leaving aside broader and important questions about how collected data is used by the app provider and how that data may, in turn, be aggregated, manipulated, and analysed to uncover further patterns with resultant observations fed back to the health care and commercial sectors, the normalisation of the use of such tools as a replacement for or better than an individual's personal observations is problematic for a range of reasons. These reasons include the fact the provision, interpretation and predictive outcomes are always open to inaccuracies whether due to messy or inaccurate initial data, due to underlying programming assumptions and parameters that might amplify particular discourses over others or require categorisation actions that render some groups as invisible or less powerful, due to opaque machine learning formulations and possibly erroneous rules, or simply that nuance or subjective or alternate interpretations are not made available when the prediction is made on the basis of rigid data collection categories. However, these possibilities are not open to scrutiny or broader interrogation: in many cases, they are accepted uncritically and then acted upon.

> *Big data enables a universalizable strategy of preemptive social decision making. Such a strategy renders individuals unable to observe, understand, participate in, or respond to information gathered or assumptions made about them. When one considers that big data can be used to make important decisions that implicate us without our even knowing it, preemptive social decision making is antithetical to privacy and due process values. (Kerr & Earle, 2013, 71)*

These pre-emptive decision making possibilities can have important ramifications for the child's developmental, educational and relational future opportunities and pathways. Yet these ramifications are not transparent or easily critiqued.

Captured at school (Educational Data Mining)

Data analytics using predictive algorithms and modelling are also well entrenched in the education systems and educational discourses at all levels – from childcare (Willson, 2019) through to the university sector (Knox, 2017; Clow, 2013). These analytics extend from the analysis of student text, student progress, peer interaction, personalisation of learning tasks and assessment, broadening out to include cognitive, behavioural and emotional analysis. Indeed,

> *Educational data scientists are becoming new kinds of scientific experts of learning with increasing legitimate authority to produce systems of knowledge about children and to define them as subjects and objects of intervention. (Williamson, 2016:401)*

Ben Williamson (2016) explores the multitude of, what he refers to as, biopolitical pedagogies increasingly employed within the education sector. These pedagogies situate data extracted through biometric devices and techniques within interpretative frameworks drawn from psychology, physiology and neuroscience to explain, predict and anticipate learning and developmental outcomes. By extending the sphere of educational influence beyond simple learning analytics derived through online assessment, monitoring and delivery through personalisation practices, the potential sphere for possible identification, prediction and intervention into the child's development is expanded to bring bodies, emotions and minds into a data enhanced educational approach. These interpretations can be at a remove from individual educator's or carer's own observations and interventions in relation to a particular child's learning, instead undertaken in a pre-emptive, presumptive and anticipatory manner as a result of correlation with an identified pattern or behaviour derived from large aggregated data sets: a just-in-case scenario.

Education providers are increasingly reliant on data-capturing commercial devices and providers of services for the provision and analysis of their educational activities across all age groups from childcare, kindergarten through to secondary and tertiary education although the nature of the activity undertaken and resultant analysis may differ. The increasing demand for interactive and engaging content underpinned by the argument about the importance of engaging different learners through fun, interactive and personalised learning activities compels educators to acquire and use online educational games and activities provided by third-party commercial providers. These third-party providers collect and may disseminate or share data on children's activities with little control over this disclosure by parents or children or indeed the education provider. Relatedly, the education providers themselves seem to be relatively opaque as far as their information data collection activities of their learners' activities (and that of parents) and the use of that data. For example, a search undertaken by this researcher in late 2018 of a number of West Australian public school websites and the state's education department web profile could not locate any evidence of a privacy or information disclosure policy to assist in interpreting the use of data collected through commercial learning management systems or applications and any data analytic or predictive activity that might be undertaken by either public or commercial entities. There were certainly no disclosures to that effect displayed.

The conflation and intermingling of spheres of activity – commercial and educational, commercial and health, public and private -not only offer opportunities for deeper and more complex data collection, aggregation and analysis, including prediction, they also extend the coverage and potential impact of the predictive application to children's futures. According to a 2012 Federal Trade Commission report, the range of data collection practices by commercial apps targeted at children is extensive and the level of disclosure of this data collection and distribution activity available to parents is inadequate. The report noted that "nearly 60% (235) of the apps reviewed transmitted device ID to the developer or, more commonly, an advertising network, analytics company, or other third party" yet "…., only 20% (81) of the apps reviewed disclosed any information about the app's privacy practices (Mohapatra & Hasty, 2012: 6).

Issues with predictive techniques

The range of issues with the application of predictive techniques have been touched on in the above discussion and in various literature elsewhere (see for example, Willson, 2019; Crawford & Schultz, 2014; Dencik, Hintz, & Carey, 2017; Andrejevic, 2017). There are clearly benefits to predictive techniques where, for example, attention is drawn to the likelihood of an adverse event such as a detrimental health outcome that might be prevented or alleviated as a result of either intervention or by increasing vigilance and resultant monitoring. However, there are a number of things to be mindful, and that require critical awareness in terms of the aims, context, and process when evaluating predictive approaches.

Aims and context

Aims denotes the underlying rationale for the predictive analysis being undertaken. This may be intentional – deliberately intending to find a way to determine particular outcomes - or accidental by machine identification or unanticipated or unforeseen patterns but seen as useful and actioned on that basis.

In critically assessing predictive analytics and their aims, context becomes important as the analytic aim or intent is entwined with cultural and social expectations and power differentials. A health context with the aim of enhancing child health outcomes (Ananthaswamy, 2017) is innately different to the use of child health data by an insurance company interested in identifying future risk and possible premiums or a commercial company interested in selling child health monitoring products. Yet the possibilities for delineating the boundaries between these two contexts – health and commercial – in their collection and use of data for predictive analysis becomes increasingly unclear where not regulated.

Different child and family cohorts may be subject to different types and levels of surveillance, with different types of predictive intents and outcomes likely. These are coupled with cultural assumptions, and disciplinary discourses as to what is normal, desirable or commodifiable. For example, the surveillance and predictive intent targeted at welfare recipients in order to identify children at risk will differ in nature but also in consequence, to the types of predictive analytics targeted at the purchasing practices of wealthy parents who can be influenced by their children to purchase particular products. This targeting highlights some cohorts and occludes others from consideration or participation.

Process

The processes employed in predictive analytics are important also because if the underlying data (often messy and drawn from different domains with different underlying parameters) is incorrect, inadequate, partial or biased then the outcome will be also. However, the capacity to check these processes is limited: machine learning techniques are opaque, the rationale for decisions and outcomes frequently unclear and unable to be interrogated. A health professional can be questioned about a treatment plan and advise on the research that informs that decision, a machine learning recommendation is not open to this level of interrogation or interaction – at least not yet. This opacity will become even more comprehensive with the increasing adoption of machine learning and artificial intelligence. The immense scale of data sets employed means a reliance on technological calculation is automatic as human calculation can be too time consuming and costly (if even possible).

Predictive techniques encourage the conflation of correlation with causation: however, the identification of patterns does not automatically denote any particular causal relationship exists as a result. They also have the capacity to replicate or amplify particular assumptions simply by the programming and attention to particular characteristics or data sets based on flawed assumptions. As Dencik et al (2017: 12) note,

> *Algorithms may create self-fulfilling prophecies whereby the targeting of certain groups in the initial analysis raises their visibility in all future calculations while obscuring other forces at play.*

This obscuration potentially distorts predictive accuracy and applicability impacting upon the decision making and application of the outcomes.

Moving forward

For contemporary children whose lives are increasingly datafied from the outset (i.e. from birth or, increasingly, even before birth), predictive potentials and consequences are amplified exponentially. Questions about what choices become available to them or not, for what reasons and what recourse they may have to change these opportunities and pathways become an increasingly pressing consideration. In a comment about the general population, Andrejevic (2013: 297) notes,

> *Every message we write, every video we post, every item we buy or view, our time-space paths and patterns of social interaction all become data points in algorithms for sorting, predicting, and managing our behavior. Some of these data points are spontaneous, the result of the intentional action of consumers; others are induced, the result of ongoing, randomized experiments. The complexity of the algorithm and the opacity of correlation render it all but impossible for those without access to the databases to determine why they may have been denied a loan, targeted for a particular political campaign message, or saturated with ads at a particular time and place when they have been revealed to be most vulnerable to marketing.*

These observations are even more relevant in the case of children who have less capacity to control the data collection and the predictively motivated decision-making that is undertaken yet has real impact on their lives. It is also more relevant given the capacity to collect data from conception onwards offering future potential for extensive profiles to be generated. Moving forward, mechanisms to interrogate, to make transparent and to contest data predictions or interventions and to highlight opportunities denied or offered as a result will need to be developed and critical literacy in relation to data collection and predictive practices will need to be acquired by all. Some nations and governance entities are putting in place overall regulatory measures to address individual data privacy management, data collection and data analytic practices but these are partial, situated as responsive to current technical possibilities and do not accommodate techniques and data predictive capacities yet to be developed. Until that time, ongoing questioning of children and their parents' agency in these predictive environments requires critical attention.

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