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DECODING RISK: MAKING SENSE OF PREDICTIVE DATA ANALYTICS

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Introduction

Researchers have increasingly recognized the need to investigate algorithmic and data-driven technology, practices, and culture (Gillespie 2014, Beer 2015, Striphas 2015). Due to their powerful position in decision-making processes, many scholars have drawn attention to the social construction of algorithms (Martin and Lynch 2009, Anderson 2012, Gitelman 2012) and emphasized the importance of unpacking how algorithms work by opening up the “black boxes” through which algorithms turn data into knowledge and decisions (Pasquale 2015).

Here, I suggest that understanding the way in which users make sense of algorithmic output is as important as the affordances contained within the technology itself. In many cases the work of algorithms and analytics are mediated through the culture and practices of various sectors, professions, and workplaces. I explore the implications of predictive analytics by examining their use in context. Do data analytics function as prognostications of the future? How does the presence of predictive technology shape judgement in context? I approach these questions through an examination of the ways in which clinicians integrate predictive analytics into the local culture and practices of a neonatal intensive care unit (NICU). I find that far from providing unquestionable readings of the future, predictive risk scores are integrated into a constellation of signs and intervene in the process of care in particular ways. I describe these processes as *conditioned reading*, *accumulative reading*, and *retroactive reconditioning*. I suggest that these particular processes occur in response to the cultural dominance of *evidence-based medicine*.

Data and Methods

During 2015-2016, I spent eight months regularly observing the use of Horizon at Eastern Hospital¹. Conceptualized as an early warning system, Horizon uses patient vitals to calculate the likelihood that an infant will develop a life-threatening infection within the next twenty-four hours. I conducted 60 hours of observation and 11

¹ The names of technology, individuals, and locations have been replaced by pseudonyms.

interviews with the users of Horizon. Observations consisted of shadowing individual physicians as they conducted rounds, shadowing individual nurses throughout shift work, and observing the unit as a whole from the nurses' station.

Horizon and Three Ways of Knowing

Horizon is one of many signifiers in the NICU through which clinicians make judgements about care. Horizon displays a risk score between 1 and 7 for each infant. I find that clinicians integrate these predictive risk scores through the following three interpretive processes.

Conditioned Reading: Focusing on deviations from expected norms and behavior, clinicians interpret Horizon in light of their experience with the individual infant for whom they are caring. As Christina described:

"I think you just learn...what their trend is. I get report from a nurse whose never had the baby, and they're like, "Oh my gosh, their Horizon is 3." And I'm like, "Oh no, it goes to 3 every night, don't worry, it'll come back down." Like kind of like that. We kind of learn their trend."

Christina's approach epitomizes the processes that I witnessed during observations. Clinicians consistently told me about how they make judgements about when to react to a change in Horizon and when to ignore it. As Robin told me, she always asks herself, "okay, do I believe Horizon in this kid or not?" That judgement of the Horizon risk score is based primarily on the clinician's existing experience with a particular infant or experiential information passed on from other clinicians.

Accumulative Reading: While the developers intend Horizon to be an early warning system, it more commonly helps to reinforce or dissuade *existing suspicions* of infection. Respondents rarely articulated experiences where an increase in the Horizon score was the first and primary indicator of infection. They were more likely to tell me about instances in which they noticed Horizon after the onset of other symptoms or simultaneously with other symptoms. For example, consider Anthony's story of a baby that developed an infection:

"He was doing fine [...] but then near the end of our shift his residuals...say he was getting 10, his residual was 8! And it looked more bloody-ish rather than just undigested food, and I was like, "Amy, I don't know about this. This is not looking right." [...] And I was like, "Also, his stomach's a little bit rounder. It feels firm. I'm kind of concerned. This is not how he was three hours ago." [...] They didn't come around until after we'd left, but when we came back the next morning, the nurse said they did a full sepsis workup on him last night because he had a Horizon spike right after you guys left and his temperature started going up. It's those small things where you're like, oh maybe it's just a feeding thing, but over the course of two or three hours, these other things started happening."

While Anthony knew that his patient was not well, he did not yet have a particular interpretation of what was causing the symptoms. Reading the constellation of signs, which included the rise in the Horizon score, the rest of the medical team determined that the baby was ill and initiated a medical intervention.

Retroactive Reconditioning: On occasion, clinicians have experiences that cause them to recast their readings of Horizon. As Bonnie described to me:

“I know there are cases where we haven't started, you know, we haven't necessarily changed our management, and the patient has decompensated and, looking back the Horizon score was elevated, but maybe we were attributing it to something else, or maybe it's just been elevated for days, and it just wasn't a big change in the trend.”

In this case, it was only through the appearance of infection via other signs that, in retrospect, Horizon and the other symptoms were made interpretable as indicators of infection.

In sum, Horizon does not function solely as an early warning system. Instead, it enters a constellation of signs. Whether or not Horizon is interpreted by the medical staff as trustworthy and useful in a particular case can influence how the other signs within the constellation are understood. In particular, when Horizon is taken as a legitimate indicator, it can be a powerful force in shaping readings of other signs.

Discussion

The dominance of *evidence-based medicine* may explain why the interpretation of predictive analytics takes the shape of the processes discussed above. Evidence-based medicine focuses on informing practice with “a clearly defined hierarchy of available evidence” (Timmermans 2010: 309). Quantifiable and measurable information are often seen as more powerful, while narrative and qualitative descriptions are somewhat suspect.

As meaning-making beings, people must be able to account for their actions and beliefs in ways that are recognizable to others *and* themselves (Berger and Luckmann 1967). Acceptable explanations vary according to social context; different institutions have different ways of reasoning that count as legitimate (Mills 1940, Boltanski and Thévenot 2006). Therefore, clinicians must make judgements about care within the appropriate framework attached to the institution of medicine. The acceptable framework within the NICU is undoubtedly that of evidence-based medicine.

Over time, clinicians build up experiential knowledge of infants in general and of particular patients under their care. This experience attunes them to small changes and provides them with feelings about a baby's condition. These hunches alert them to potential illness, but are often insufficient for making a diagnosis. Diagnoses require evidence, usually in the form of quantifiable vitals and lab results. Horizon is powerful because it provides a quantified metric through which to make sense of the qualitative signs the clinicians receive through other means.

References

Anderson, C.W. (2012). Towards a sociology of computational and algorithmic journalism. *New Media & Society*, 15(7), 1005-1021.

- Beer, D. (2015). Productive measures: Culture and measurement in the context of everyday neoliberalism. *Big Data & Society* 2(1).
- Berger, P.L., & Luckmann, T. (1967). *The Social Construction of Reality: A Treatise in the Sociology of Knowledge*. Anchor.
- Boltanski, L., & Thévenot. L. (2006). *On Justification: Economies of Worth*. Princeton UP.
- Gillespie, T. (2014). The relevance of algorithms. In Gillespie, Boczkowski, & Foot (Eds.) *Media technologies: essays on communication, materiality, and society* (167-194). Cambridge: MIT Press.
- Gitelman, L. (2013). *"Raw data" is an oxymoron*. Cambridge: MIT Press.
- Mills, C.W. (1940). Situated actions and vocabularies of motive. *American Sociological Review* 5(6):904–913.
- Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information*. Cambridge: Harvard UP.
- Striphas, T. (2015). Algorithmic culture. *European Journal of Cultural Studies* 18(4–5), 395–412.
- Timmermans, S. (2010). Evidence-based medicine: sociological explorations. In Bird, C.E., Conrad, P., Fremont, A.M., & Timmermans, S., *Handbook of medical sociology*, (6th ed). (309-323). Nashville: Vanderbilt UP.