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When predictive analytics goes wrong: what can healthcare learn from Formula 1?

Predictive analytics refers to technology that uses patterns in large datasets to predict future events and inform decisions. This article considers the challenges of this technology and how these should be considered, before incorporating this technology into healthcare settings.

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From Framingham's risk score to national early warning scores, risk prediction tools have long been used to predict health outcomes in order to optimise patient care. The recent increase in electronic patient data has seen predictive tools upgraded to predictive analytics, which is technology that uses patterns in large datasets to predict future events and drive better decisions (Watson, 2019). Predictive analytics could impact all organisational levels in healthcare, with proposed benefits for areas including precision medicine, cohort epidemiology and operational management (Watson, 2019).

The NHS Long Term Plan requires that hospitals embrace digital records by 2023, meaning that all UK hospitals could soon have the data to utilise predictive analytics (NHS England, 2019). The establishment of NHSX as the UK government unit responsible for developing best practice for NHS technology and driving technological innovation in health and social care could accelerate this. Surveys report that 88% of health executives are already using or are planning to use predictive analytics (Duncan, 2017).

Numerous industries have already embraced predictive analytics. Formula 1 racing teams have used data analytics since the 1970s to predict future events and inform race strategy. Alongside many successes, several high-profile losses demonstrate that predictive analytical technologies are not infallible. Evaluating mistakes offers valuable insights into the limitations of such technologies and how these might be addressed. Ferrari's loss at the 2010 Abu Dhabi Grand Prix exemplifies the three major challenges of predictive analytics in practice: automation bias, inadequate data and blame culture. This article discusses how these challenges might manifest in healthcare and the steps that can be taken to avoid similar mistakes.

Analytical failure at the 2010 Abu Dhabi Grand Prix

Coming into the final race of the 2010 season at the top of the scoreboard, Ferrari driver Fernando Alonso needed just a top-four finish to win the driver's championship. During races, Alonso was assisted by race engineer, Chris Dyer, and a decision support system that analysed historic and real-time race data to predict future events and calculate strategic recommendations.

Alonso maintained fourth place for the first ten laps. However, in lap 11 competitor Mark Webber was called for a pitstop, causing Ferrari's decision support system to respond by recommending two options to maintain Alonso's winning position: (1) pit at lap 11, or (2) pit at lap 15. Dyer chose option 2, a crucial error. Re-entering the track after pitting, Alonso became stuck behind his competitors on a racetrack that made it difficult to overtake. Consequently, Ferrari finished the race in 7th place, forfeiting the driver's championship title by one point.

Errors of automation bias

Race analysis showed Ferrari's loss would have been avoided if Alonso was not pitted so early (Aversa et al, 2018). In interviews, Dyer mentions contemplating his own 'option 3' whereby Alonso would have been pitted at lap 20, which looked like a much better option than the automated recommendations (Aversa et al, 2018). So why did he still choose option 2?

Dyer's awareness of Ferrari's technological proficiency made him overly reliant on the decision support system, causing him to put its recommendations above human insights (Aversa et al, 2018). Errors of overreliance are classified as automation bias, which manifests as errors of commission (following incorrect automated advice) or omission (inaction as a result of a lack of automated prompting) (Goddard et al, 2012). Dyer's mistake was a commission error.

Commission errors are the clearest consequence of automation bias in healthcare. They can cause negative consultations wherein correct decisions are reversed, following erroneous automated input (Goddard et al, 2012). A systematic review of clinical decision support system trials reported negative consultation rates of 6–11%. Reviewers presented evidence that higher task complexity and workload (both features of the medical profession) increase the risk of such errors (Goddard et al, 2012). Despite support for the use of predictive analytics, technology is not infallible, and predictive technologies could introduce novel risk to patient safety if automation bias goes unaddressed.

The same systematic review presented research suggesting that increasing users' accountability and understanding of a machine's analytical algorithms and reasoning processes could decrease overreliance (Goddard et al, 2012). However, this evidence is not uniform. Overly comprehensive explanations of machine processes have also been found to increase overreliance by promoting excessive trust in technology (Bussone et al, 2015). One study found no relationship between accountability and automation bias (Mosier et al, 1997). Hence, this type of bias remains a concern for implementing clinical predictive analytics.

'Garbage in, garbage out'

With up to 20 terabytes of data collected per car in a racing weekend (Aversa et al, 2018), Formula 1's large datasets are often used to verify analytical accuracy. Yet Ferrari's data proved inadequate, as the decision support system lacked data regarding Abu Dhabi's racecourse and drivers other than Alonso, thereby acknowledging neither the racetrack nor the competitors when computing its predictions (Aversa et al, 2018). Consequently, Ferrari fell victim to analytics' often cited truism: 'garbage in, garbage out'.

While the NHS patient dataset is praised as one of the largest clinical datasets, the scarcity of data concerning diverse populations poses a significant challenge to predictive analytics (Rajkomar et al, 2019). Contributing factors include significant disparities in the demographic patterns of smartphones, smartwatches and other devices used to collect health data (Cahan et al, 2019) and the concentration of research and innovation in clinical centres with established technological sectors (Deeny and Vestesson, 2019). This creates sampling bias, as diverse groups are disproportionately absent from data, generating non-representative predictive algorithms that engender false positive and false negative outputs when applied to minority patients, thereby risking their safety (Cahan et al, 2019). Worryingly, most algorithms based on electronic health records fail to correct for missing data (Brakenhoff et al, 2018). It is important to highlight and address inadequate data input as a problem that could see the use of predictive analytics intensify existing health inequalities.

Greater transparency is needed to encourage data collection efforts to include marginalised communities (Zou and Schiebinger, 2018). However, the perseverance of health inequality suggests that the solution may not be simple, with some proposing mandated inclusivity thresholds to ensure representative data (Cai and Zhu, 2015). Creating 'synthetic' datasets based on real clinical data is also being explored as a method of increasing diversity and correcting bias, although its ability to accurately model health outcomes is currently limited (Chen et al, 2019).

Innovating in a culture of blame

Ferrari's decision to fire its race engineer Chris Dyer after Alonso's loss contributes to the company's history of substituting directors following disappointing results. This is symptomatic of an organisational culture that favours scapegoating, rather than learning from mistakes. This culture likely contributed to Dyer's decision to forego his own option 3, for the less favourable automated output. Although implementing his own insight would have been unproblematic if victorious, Dyer feared backlash from Ferrari if ignoring the decision support system had not been successful (Aversa et al, 2018).

Key points

- Predictive analytics is technology that uses patterns in large datasets to predict future events, in order to optimise decision making.
- Studying analytical failures from Formula 1 racing offers valuable insight for considering the successful implementation of predictive analytics into healthcare.
- Automation bias, inadequate data and blame culture challenge the ability to safely and effectively incorporate predictive analytics into healthcare.
- Further research is needed to identify additional challenges and solutions, in order to avoid historic failures of predictive analytics being emulated in healthcare settings.

A similar blame culture has been described within the NHS, suggesting that doctors could face similar pressures when using predictive analytics (Wise, 2018). Some UK doctors already report practicing defensively, meaning they make decisions to protect against litigation, as a result of fearing unfair blame for errors made because of systemic failings (Wise, 2018). Defensive practice is likely to extend to predictive analytics and this will impede its clinical implementation.

Defensive practice could see physicians deferring to automated recommendations that they lack confidence in, rather than trusting their own clinical judgement. Alternatively, physicians might object to predictive analytics because they fear blame and litigation. Both would negatively affect patient care. Blind judgements could directly compromise patient safety while the fear of using these technologies would prevent the realisation of predictive analytics' numerous benefits for healthcare. Furthermore, blame culture could obstruct quality improvement by discouraging clinicians from reporting adverse events (Wise, 2018), allowing issues pertaining to predictive analytics to persist, rather than being acknowledged and addressed.

Conclusions

The push for NHS providers to embrace predictive technologies grows stronger, but the challenges of implementation cannot be ignored. Just as predictive analytics learns from experience and predicts future events, medical innovators should not overlook past mistakes when envisaging the impacts of predictive technology. While clinical case studies are presently scarce, learning does not need to be limited to medical experiences. Ferrari's mistake highlights the challenges of automation bias, inadequate data and blame culture, that threaten the efficacy and safety of implementing predictive technologies in healthcare. These issues are yet to be addressed and are just a few of the challenges that require consideration. Looking forward, greater research into the challenges of incorporating predictive analytics is essential, if healthcare is to avoid repeating the past failures of other industries.

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Conflicts of interest

Mr SFH Shah is an Innovation Associate at ImproveWell and Mr Z Sheridan is a Business Development Analyst at ImproveWell, which is a staff engagement tool that drives quality improvement processes in healthcare.

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