

The Approaching Singularity in Medicine: When Computers Exceed Physician Performance



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This is to acknowledge that Ruben Amarasingham, M.D. has disclosed that he does not have any financial interests or other relationships with commercial concerns related directly or indirectly to this program, beyond being an employee of PCCI, a non-profit research and development corporation that specializes in predictive modeling software. Dr. Amarasingham will not be discussing off-label uses in his presentation.

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Purpose & Overview:

In this talk I will be discussing the emerging area of electronic predictive analysis, and machine based diagnosis and recommendations and the implications, problems, and considerations for the practice of medicine, particularly if such machine based approaches exceed the performance of physicians.

Objectives:

1. An overview of machine intelligence in medicine
2. Increasing need for machine intelligence in medicine
3. Implications of machine intelligence for clinical practice, policy, and ethics

Biosketch:

Ruben Amarasingham, MD, MBA is Associate Professor in the Departments of Internal Medicine and Clinical Sciences at the University of Texas Southwestern Medical Center, where he also serves as the Director of Biomedical Informatics for the NIH Center for Translational Sciences (CTSA) award. He is also Founder, President and CEO of PCCI, a non-profit research and development corporation in Dallas, Texas that specializes in real-time health predictive and surveillance software. He has conducted and published studies in health IT evaluation, EMR-based enterprise-wide quality improvement, and real-time health predictive analytics and has won more than \$20 million in extra-mural research funding in these areas. Dr. Amarasingham co-invented the Pieces™ software system, an electronic coordination and clinical decision support system that forecasts adverse clinical events using real-time EMR data. Dr. Amarasingham received his ScB from Brown University and completed his MD and Internal Medicine residency at the University of Texas Southwestern Medical Center. He received post-doctoral training in medical informatics and operations and health services research as a Robert Wood Johnson Clinical Scholar at the Johns Hopkins Medical Institutions. He completed his MBA at the Johns Hopkins Carey School of Business.

The US healthcare system faces significant challenges. The system struggles with high cost, poor quality, and uneven performance (1-3). It is possible however that real-time, artificially intelligent (AI) predictive modeling systems driven off electronic medical record (EMR) systems could help the healthcare systems achieve the Triple Aim of improving health of populations, quality of care and reducing costs (4).

Successful applications of real-time predictive models in healthcare exist. We recently reported a significant drop in readmission rate for heart failure patients in a safety net hospital after implementing an EMR based readmission prediction model (5), and an unreported, larger multi-center trial in adult medicine patients has concluded successfully with similar results. Researchers in Kaiser Permanente developed a predictive model of the risk of early-onset sepsis in newborns, and concluded that the nation could reduce antibiotic treatment in up to 240,000 newborns each year using this model (6).

In most other industries and sectors of the economy, predictive algorithms play key roles in decision support, risk modeling, fraud detection, targeted advertising, and trend prediction (7). In aviation and in national security, automated tools are used to perform data vigilance, surveillance, fusion, filtering and predictive analytics to assist human decision makers who would be unable to process the volume and stream of data otherwise. Similarly, automated predictive algorithms have been used to perform targeted advertisements that are more closely aligned with customers' interests and preferences (8).

However the increasing emergence of computers in medicine may produce potentially disruptive dynamics in the medical profession and within the physician-patient relationship. These potentially far reaching implications have so far received little attention.

How well we manage some of these dynamics will have major consequences of the ultimate roles computers and artificial intelligence will play in healthcare systems. In this paper we explore some of these dynamics and their implications, and propose constructive ways to manage such potential to ensure that we reap the full benefits of clinical AI and effectively manage the inherent risks.

Reliance and trust in predictive models

Trust in or distrust of technology is important because of the potential to alter interpersonal relationships between physicians and patients and the risk of adverse health care processes and outcomes. Recent research has indicated that user trust in technology in healthcare can result in appropriate use, inappropriate use, or rejection of the technology (9). New technologies in healthcare are usually heavily regulated and often standardized to ensure a certain level of safety and efficacy before such new technologies are allowed to enter the system. Such assurance is important for physicians and patients to form an appropriate level of trust in these new technologies based on their proven levels of safety and efficacy.

Predictive analytics, on the other hand, do not yet have such a well-defined regulatory framework. Published models rely on the peer review process to ensure a certain level of quality, although such mechanisms are far weaker than the regulatory framework for pharmaceutical products and medical devices. Moreover, many commercially available models have not gone through such peer review, making it more difficult to evaluate their quality.

As a consequence of this lack of regulatory framework and the rapid development of the field, the quality of the available models varies widely, and specific indicators of quality are not readily accessible. These problems make it difficult for physicians and patients to develop

appropriate levels of trust in these models. This can result in too much, too little, or misplaced trust in predictive analytical models.

Too much trust may result in unwarranted and inappropriate reliance on predictive analytic models resulting in adverse health outcomes. More specifically, the physician-patient pair may make critical care decisions based on predictions of the relative benefits and risks of different treatment options. If the physician-patient pair blindly follows the prediction of the model without sufficient understanding of the performance indicators of the model (such as false positive and false negative rates), or without access to such indicators, the wrong decision could be made based on the results of these models, resulting in adverse outcomes.

Such adverse outcomes in turn may create the misleading impression that all predictive analytical models are unreliable, resulting in mistrust and under-utilization. In an environment with rapidly increasing number of models and a lack of readily accessible quality indicators or uniform quality standards, such circle of over-reliance, adverse outcomes, and mistrust and under-utilization may be especially damaging to the long term health and development of predictive analytics. As the recent crash of the global financial system showed, over-reliance and too much trust in sophisticated (financial price and risk prediction) algorithms without proper understanding of the underlying assumptions and inherent risks of such algorithms is perilous.

Predictive models and clinical decision making

Historically, clinical decision making was almost solely the province of physicians, hence the adage, “the doctor’s pen is the most expensive equipment in the hospital”. Over time, the domain of decision making expanded to include nurses and paraprofessionals, and more recently, patients themselves. In this new paradigm of shared decision making, providers and patients

decide together on a plan consistent with medical science and personalized to each patient's needs, values, and preferences (10).

The physician's ability to offer a plan consistent with medical science is enhanced by the development and adoption of various technologies, such as the imaging machines and genetic testing instruments, as these technologies usually provide more accurate information directly relevant to patient care. With the rapid development of predictive analytics, it is likely that clinical decisions will be increasingly driven by electronic predictive algorithms trained on vast amounts of data.

Unlike previous generations of healthcare technologies that assisted and reinforced the shared decision making model, however, predictive analytics can upset the current clinical decision making model and redefine the clinical decision making framework. Unlike previous technologies whose aim is to provide more accurate information to aid the decision making, predictive analytics may include artificial intelligence or decision making rules capable of supplementing, and eventually replacing, the decision making capabilities of the physicians.

There is evidence to suggest that human beings do not perform well in healthcare related tasks involving predictions with uncertainty (11,12). With the increasing sophistication of predictive analytic models, these models could be more accurate than most medical professionals in making judgments about diagnosis or therapeutic efficacy. Recent developments, including competition between computers and professional chess and Jeopardy players, are early indication of this possibility (13,14).

The arrival of increasingly more sophisticated models that may rival or even exceed individual physicians in many aspects of professional knowledge required for clinical decision

making raise important questions. Some that will need to be addressed regard the proper role of predictive analytical models in clinical decision making, and how to establish a new clinical decision making framework where the physician, the patient, and the model work in harmony to arrive at the best decision. Who, for example, should have the ultimate authority in making difficult decisions, especially when the professional judgment of the physician differs from the conclusions of the data driven models? What roles should the physician play when most aspects of his professional judgments can be replaced by predictive and data driven models? Failure to address these questions and to establish such a clinical decision making framework may result in confusion on the appropriate use of these models.

We would suggest that the physician-patient pair retain the ultimate clinical decision making authority, with substantial input from a variety of decision making tools including predictive and data driven models. An appropriate analogy of the relationship between physicians and these predictive and data drive models could be the relationship between flight pilots and the computer driven instrument panels in modern day airplanes: the pilot is still in charge, however the way he operates and the skill sets required differ substantially from pilots of earlier days.

Predictive models and the physician workforce

Adjustment in the physician workforce usually follows arrival of breakthrough technologies in healthcare. New opportunities are created for physicians with new skill sets to interpret the findings of these technologies. While the technologies may also make some skill sets obsolete, predictive analytics are likely to create new opportunities for medical professionals with the skillsets to develop, implement, and interpret these models.

It is also conceivable, however, that models may replace physicians in the way automation replaced many workers in the manufacturing sector. Or less dramatically, professionals with less training (e.g., physician assistants or nurse practitioners) or physicians in countries with far cheaper costs (e.g., India) and armed with predictive analytics may replace groups of physicians elsewhere.

In fact, with the current need to save cost, reduce variation and increase consistency, it may be inevitable that predictive analytics will replace at least some portion of the functions performed by physicians today (15). The physician workforce is expensive, variable and inconsistent, subject to bias and error, with limited availability, and need to rest, vacation, and ultimately retire. Sophisticated intelligent models, on the other hand, do not have any of these shortcomings and may become irresistible in a system with increasing demand and insufficient resources. Automation or outsourcing are already commonplace in manufacturing and are spreading into traditionally human intensive professions such as accounting and legal, and there is evidence that this is also happening in a limited scope within the medical profession (16,17).

What roles should physicians play in the future? Should we welcome the potential of predictive analytics to save cost, reduce unnecessary practice variation, and improve productivity and quality in healthcare and embrace the replacement of all or part of the tasks currently performed by physicians, or should we take proactive actions to preserve the medical profession? Answers to these questions may have far reaching implications to the physician workforce.

Loss of critical skills by using predictive models

Physicians may also suffer loss of skills from constant use of predictive models, similar to the way many people voluntarily relinquish their ability to mapping and direction with sustained use of Global Position System (GPS) devices (18).

This issue would be most acute for new generations of physicians who start their training and career with these models. They would take their existence for granted, and unless deliberate efforts were made, they would not have the opportunity to develop and improve their skills that are readily supplied by the models. While such loss of skills may be inevitable and not necessarily undesirable, it is important to take actions to ensure that those skills are preserved at least in a dedicated portion of the clinical workforce.

How should we achieve the proper balance between utilizing the power of these models and preserving physicians' ability to operate effectively without such models? The training and operation of pilots provide a starting point for establishing an effective approach. Pilots are trained to fly airplanes with the help of increasingly advanced technologies, and as a result they can fly bigger airplanes with more stable performance. On the other hand, they are also trained to be able to override these technologies or to fly without them, as there is always a possibility where a catastrophe would dictate manual control. A similar training framework could work for physicians, although the details would need to be worked out.

How will predictive models be used?

Major innovations usually achieve their full potential with the emergence of appropriate supporting infrastructure and workflow that utilize the strength of the innovations and protect against the weaknesses. In healthcare IT more generally, diffusion of EMRs was relatively slow until recent federal government initiatives and incentives were launched. Counting back two

decades since the first availability of EMRs, this long, slow diffusion is similar to that of other complex electronic and computing devices such as enterprise-level relational databases (19).

For example, the improvement in productivity by using personal computers was only achieved after complementary capital investments and organizational changes were made and workflow re-engineering projects completed (20). Similarly, the power of predictive models can only be realized when the results of the models are acted upon appropriately by human operators – clinicians, ancillary staff and lay health workers in community based organizations - to improve quality of care, enhance patient experiences, and save cost.

Analogous complementary investments would include training in the use of predictive model outputs as part of a clinician's armamentarium. An often under-appreciated complementary input to clinical decision-making is time itself. Freeing up clinician time to work closer with input data and output results is necessary as well, if predictive analytics are to be fully used. Changing roles and responsibilities to permit front-line staff to act on predictive output in timely ways will also be necessary complementary investments. In the same way leading customer-focused service firms empower their 'at the coalface' staff to stay with a customer they predict will require some action, so too will hospitals and clinicians need to re-engineer the delivery of work.

If such complementary investments in training, time and re-engineered delivery processes and roles are not made, then the field of predictive analytics could face similar risk as the field of information technology more generally. As Brynjolfsson pointed out twenty years ago, there is an apparent contradiction between the labor-saving productivity promise of information technology abundantly implemented in the workplace, and the relatively slow growth of national

labor productivity (21,22). The analogous risk with predictive models – and their promise of improvements in cost, safety and quality – is that they fail to live up to this promise without large-scale complementary investments as outlined above.

Proposed solutions

While there is no single answer to address these potential implications, implementing a suite of sensible recommendations can go a long way to ensuring the successful diffusion of predictive analytics in the healthcare system. These solutions include transparency in model development and quality, proper ethical, legal, regulatory and culture frameworks, flexible medical education system, and supportive incentive mechanisms.

Transparency in model development and evaluation

Transparency can foster healthy development and diffusion of predictive analytics in healthcare in significant ways. First, transparency can help establish the necessary infrastructure for predictive analytics by creating environments that encourage and facilitate collaboration and exchange of ideas among diverse stakeholders. Innovative ideas, advanced modeling techniques and algorithms, standardized databases, and the next generation of clinicians and scientists are more likely to emerge in an open environment. Convergence to standards and deployment of best practices within the industry is more likely to happen if openness prevails.

Model transparency also facilitates the entire process of model development and implementation, including identifying and securing access to various data sources, developing the model and the secondary source code to report results of the model, instantiating the model in the EMR, ensuring that the instantiation is appropriate and actually usable, and modifying clinician workflow to incorporate the model into practice.

Finally, transparency can help establish solid foundations for the field of predictive analytics. Transparency would constitute a key ingredient of the legal and ethical framework to guide the development and utilization of these models. It would also facilitate the emergence of a solid methodological foundation by enabling researchers in various disciplines to communicate and exchange ideas to establish a common, well accepted, understanding of the appropriate place of predictive analytics in these disciplines. The medical profession will also be able to appropriately integrate results of these models with other relevant information sources, when details of the models, including the variables used, and the modeling methodology, are made available to them.

Appropriate ethics, legal, regulatory, and culture frameworks

Many potential challenges with predictive models are direct consequences of the lack of clearly defined and well accepted ethics, legal, regulatory, and culture frameworks guiding the development and utilization predictive analytics in healthcare. We need well-thought out, widely agreed upon frameworks that integrate perspectives of the medical profession, with a well-defined set of performance indicators to evaluate models that are readily accessible, a clear set of guidelines on the appropriate roles and responsibilities of the physicians, the patients, the models, and a clear assignment of liabilities for adverse outcomes.

The need for such frameworks and some specific details of such frameworks are discussed in detail elsewhere in this special issue. It is important, however, to emphasize the importance of having such frameworks sufficiently early in the diffusion process to ensure healthy development of the field.

New model of medical education

The medical education system is designed to provide physicians with the skills they would need to operate in the future, and a flexible education system that can prepare future physicians for the opportunities and challenges with predictive analytics can go a long way to pave the way for the smooth diffusion of predictive analytics.

For example, it is essential to endow physicians with a solid understanding of the foundations of predictive analytics, both the underlying principals and how to appropriately utilize them in clinical practice. This is clearly more than just an understanding of statistics, biostatistics or regression analysis. A well trained physician should understand how these models work, when and how to use them in practice, and to have actually practiced on such models while in training, much as students already gain substantial exposure to computer- and mannequin-based simulations. He or she should also be able to operate with or without the aid of these predictive models. To achieve these goals, the current curriculum should be revised to incorporate these elements. Indeed, medical students and clinicians in training could usefully adopt many of the practice-rehearse-review approaches of learners in battlefield and aerospace operations. Similar to the way pilots are trained using flight simulators to refine and retain their skills, more emphasis should be placed on “training to do” (23).

Appropriate incentive mechanisms

It has been argued that a large portion of the challenges of our healthcare system can be traced back to problematic incentive mechanisms; examples include over utilization of expensive interventions, under-utilization of more preventative interventions, distortive fee structure, and under-supply of general practitioners (24,25). While there are many reasons why our current healthcare system is comparatively the most expensive and among the least effective when

measured using population level outcomes among developed countries, historic and current incentive mechanisms play a significant role.

Another factor is reimbursement policy of various payers. The payers' reimbursement policies have a direct impact on the adoption of various technologies, and it is likely that appropriate policies could shape the adoption and utilization of predictive analytics in a significant extent by using incentive as instrument. For example, the current Electronic Health Records (EHR) Incentive Programs and the readmission reduction program at CMS has induced widespread development and adoption of EHRs and predictive models of readmission (26,27).

It is likely that incentive frameworks will need to reflect the crucial role of predictive analytics. We speculate that payors could insist – analogous to an Underwriters Laboratory UL mark – on having predictive analytics involved in care processes. The rise of third-party furnishers of payor-compliant decision-support for ordering investigations and imaging (e.g. Anvita) may be a suitable illustration of payor-provider collaboration on automated decision-support. Other incentive-based mechanisms that could play a major role in driving the diffusion of predictive analytics include simple value-based qualifiers. Higher reimbursement for claims incurred on a pathway with embedded predictive analytics may incent earlier adoption.

Discussion

This paper has surveyed some of the potentially unintended and troubling scenarios that might arise with the overly rapid and widespread adoption of predictive analytics. These scenarios are by nature hypothetical; many may not occur, while other scenarios may also emerge. Our objectives are to outline the underlying dynamics that would give rise to such scenarios and to provoke discussion on these dynamics, rather than to offer specific predictions

of what will or will not happen in the future, or to prescribe specific solutions to address these issues. We based our analysis on a review of current literature, on our experiences in developing and implementing predictive models, and on our interactions with a broad range of stakeholders.

While the scenarios we discussed may or may not occur, we believe that the potential dynamics that spawn such outcomes deserve more attention than they currently receive. If we manage them proactively with carefully considered plans at the public policy, the vendor and the provider levels, we stand to reap the benefits of predictive analytics at minimum risk.

Conversely, some of these dynamics may manifest themselves in disruptive ways with unpredictable and negative consequences for healthcare delivery.

Our experiences at the Parkland Center for Clinical Innovation (PCCI) offer first hand experiences of the potential of predictive analytics to improve our healthcare system, the potentially disruptive ways these models can pose, and some successful strategies to address them. For example, we recently implemented a risk prediction model as part of the readmission reduction program at Parkland and other Texas institutions. The results are compelling, and clearly demonstrate the potential for such models. In one of such programs, the program reduced readmission rate with minimum additional resources by effectively aligning resources with patients in greatest need for such resources (5).

Such improvement did not come automatically with the deployment of the predictive model. In line with some of the recommendations in this paper, we made significant complementary investments. We made significant changes to our workflow and clearly defined the roles of physicians, case managers, nurses, as well as fine tuning the predictive model over

time. Without awareness of the risks, and without such proactive planning and actions, such improvement would have not been possible.

As practitioners working at the intersection of healthcare, predictive analytics and innovation, we are optimistic that predictive analytics can help achieve the Triple Aim of improving outcomes, enhancing patient experiences, and reducing cost (4). But we are pragmatic and keenly aware of the challenges and risk of failure that widespread implementation may pose in our current system.

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