Editorial

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Biographical notes: Ning Jackie Zhang started his faculty career in the Doctoral Program in Public Affairs in University of Central Florida, Orlando, FL, after graduating from Department of Health Administration with a PhD in 2003. He got tenured in 2009 and continued to teach as an Associate Professor till 2014 when he moved to the Seton Hall University, South Orange, NJ. At the SHU, he was promoted to a Full Professor in 2014 and the Associated Dean for Academic Affairs in 2018. He became the Editor-in-Chief of the *International Journal of Computational Medicine and Healthcare* in 2018.

Joseph Conte is currently the Executive Director of the Staten Island PPS tasked with carrying out the New York Medicaid Redesign Waiver. He also leads the National Collaborative Consortium for Substance Use Disorder. Immediately prior to the PPS, he was the Senior Vice President for Administration at the Richmond University Medical Center. He also served as the Executive Vice President at the Catholic Health Service of Long Island and Senior Vice President of Quality at NorthWell Health System following time at St. Luke's/Roosevelt Hospital and Beth Israel Medical Center. He has served as an Adjunct Professor at the Columbia University Mailman School of Health and Wagner College School of Business Administration.

Healthcare continues to reach new heights in managing previously untreatable conditions, and technology has played a major role in these advances. Miniaturisation of interventional tools, implantable devices, imaging advances, precision radiation and proton therapy, laboratory robotics, wearable monitoring devices and medication adherence trackers are widely employed. Telemedicine advances have removed geographic barriers to care in every service line from stroke, cardiology, ICU, dermatology and psychiatric care. Computer assisted diagnostics and treatments like CAR T cell therapy are in wide-spread use. Applied technology is revolutionising care and public policy officials are employing big data, genomics and population level data into public health initiatives, vaccination designs and disease surveillance. Electronic health records, once a poorly adopted technology, are now universally implemented world-wide.

Yet, a profound paradox exists – as these technological advances continue so do unsustainable trends in total cost of care. In the USA for instance, the national healthcare bill was a staggering $3.5 trillion in 2017 (https://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/nationalhealthexpenddata/nhe-fact-sheet.html). In an added twist, quality outcomes remain far below those of other industrialised nations and life-expectancy lags significantly, suggesting that spending and quality are not correlated (https://www.healthsystemtracker.org/chart-collection/health-spending-u-s-compare-countries/#item-start). In an MIT technology review article (https://www.technologyreview.com/s/518876/the-costly-paradox-of-health-care-technology/), Johnathan Skinner captures the essence of the conundrum, "In every industry but one, technology makes things better and cheaper. Why is it that innovation increases the cost of health care?" The conclusion reached with the help of Harvard's Kennedy School of Government researchers, whose data Skinner reported, was one that the will shock no one in the industry – it is not just 'technology' that is driving our rising healthcare costs; it is the type of technology that is developed, adopted, and then diffused through hospitals and doctors' offices often fuelled by device manufacturers and competitive health systems blindly competing for high margin procedures. Most of the spending growth is generated by a technology category that includes treatments whose benefits are small compared to traditional care or supported by little scientific evidence. These include expensive robotic surgical treatments, proton-beam accelerators and aggressive treatments for end-of-life patients such as L-VADs. Unlike many countries, the USA pays for nearly any technology and at prices that fail to demonstrate value differential from standard care. Other industrialised nations likewise are struggling with expensive advances in healthcare technology that parallel this phenomenon. Interestingly, other nations spend more on social care than medical services and seem to perform better in quality outcomes and longevity. Finding a balance between the need for management of social determinant of health factors and advanced clinical technology is an important challenge and big data and informatics are at the centre of this issue.

Throughout the dizzying advanced technology pursuit, healthcare informatics has carved itself out for itself a valuable niche. Now that it is universally accepted that a person's zip code may have as much to do with their health outcomes as their access to medical service, informatics is coming into its own. The study of large datasets and sharing of information between health networks and public/private health exchanges is finally yielding population health benefits and directing investments and resources where return on investment is measured in quality of life. As payment models change, population health and prevention are receiving more focus. There is a growing need for technology in this arena/field such as patient facing apps that engage individuals in behaviour change, medication and chronic condition adherence, remote monitoring, and chronic disease management. All these applications are proliferating and show great promise to improve patients' quality of life and reduce costs throughout the continuum of the life cycle. Massive investments in technology that benefit the few at extraordinary cost will see the sources of capital previously available dry-up as value-based payments move from government payers to commercial insurers. It is in this context that the next innovators in technology and patient care will find their opportunity.

According to the *New England Journal of Medicine*, up to 30% of the entire world's stored data is generated in the healthcare system (Huesch and Mosher, 2017). Thus, the healthcare industry has an advantage and a necessity to utilise data to address health problems and disease treatments. Interests in data intelligence and information extractions, including machine learning, artificial intelligence, natural language processing, and deep learning, have grown substantially among healthcare providers and organisations. Some successfully implemented applications include diagnosing diabetic retinopathy (Gulshan et al., 2016), autism subtyping through comorbidities clustering (Doshi-Velez et al., 2014), identifying lymph node metastases from breast pathology results (Golden, 2017), phenotyping from observation data (Pivovarov et al., 2015), detecting malignant skin lesions using dermotoscopic medical images (Esteva et al., 2017), automatic fall detection among geriatric patients (Haque et al., 2017) and automated analysis for bone scintigraphy (Inaki et al., 2019). The rapidly increasing volume and complexity of the data in biomedical and health fields present unprecedent opportunities for new modelling algorithms, methods and innovations in disease diagnosis, treatment and drug development. At the same time, mounting challenges continue to surface as healthcare providers have higher expectations regarding the accuracy, flexibility and efficiency of the data intelligence to support more insightful knowledge and quicker decision making.

Meanwhile, voices have been raised regarding the overly optimistic uses and misuses of data sciences and informatics in healthcare and other industries. Some major criticisms include:

1. Data quality and adequacy for data analytics. The data collection platforms including EHRs across hospitals are incompatible and fragmented so that data integrations of multiple genetic, biological, clinical, imaging and administrative datasets are limited.
2. Simulation and modelling approaches. The conclusion validity of the results depends on the validity of the simulation and modelling. The rigorousness of the methods directly affects the trustfulness of study results, especially when the simulation and modelling approaches are not easily presented in mathematical format.
3. Data variations and generalisability. Biomedical and healthcare data points, biomarkers and new variables grow exponentially. The results of analytics and simulations need to be updated frequently, and the generalisability of the results will always be in question as the variations of data constantly change in the real world.

The theories and applications of data intelligence are rooted in the interdisciplinary best practices of data sciences, engineering, statistics, simulations, decision sciences, and relevant areas including medicine. The fundamental goals are effective and efficient decision making and improved outcomes. In the foreseeable future, optimisation and automation may become the foci of data intelligence to meet the increasing clinical and healthcare applications. Thanks to all the authors' contributions, this special issue demonstrates some innovative data intelligence practices from theory to applications across biomedical, healthcare and clinical domains.

There are eight papers included in this special issue. The first paper entitled 'A cellular automation-based passive-acoustic technique for topological characterisation of objects in fluid with potential application to carotid artery plaques' uses 3D simulations to analyse the topological characteristics of plaque placed into artificial arteries. The presentations of images created an innovative system to provide preliminary evidence for pictorial diagnosis representations for occlusions, which could be used at ambulatory and clinic settings. The second paper entitled 'Simulation and analysis of HIV-ADs dynamics' used simulation approaches to study the HIV propagation dynamics and how the HIV virus infects and develops AIDS at the population level. The third paper entitled 'A systematic literature review of data forecast and internet of things on the e-health landscape' represents a systematic literature review to examine how the use of data forecast combined with IoT can be applied to healthcare, and how the taxonomy of IoT systems could be useful for future automation development. The fourth paper entitled 'Integrating the Kano model for optimising CPR-D training system' demonstrates the utilisations of a Kano model-based questionnaire to optimise the CPR-D training system. The fifth paper entitled 'Soup burns and the roles played by viscosity, solid constituents, epidermal thickness and clothing' developed a simulation-based methodology to predict the severity of scalds as a result of accidental soup spills. The sixth paper entitled 'Measuring the impact of certified electronic health record technology on cost, quality and safety outcomes' investigated the meaningful uses of EHR technologies and their impacts on the cost, quality and safety outcomes based on national administrative data in the USA. The last two papers address the uses of natural language processing methods in identifying metastatic melanoma compared to traditional methods and identifying biomarkers for breast cancer determinations based on the EMR data. Due to the significance and innovation of the SLP methods, a separate editorial was included to discuss the applications of the SLP methods.

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