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Update and Acceleration of Health Care Using Artificial Intelligence in Medical Treatments and Diagnostics

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ABSTRACT

Researchers support the growth of artificial intelligence and similar methods in health and medical care for the purpose of continuously improving processes. By focusing on the growth on data analytics, statistics, applied mathematics, and computer methods including machine learning, the future of health-care methods will change. The development of computerized methods and the growth of data systems produce ample materials for artificial intelligence to develop and to bring physician assistance programs to enable continuous improvement resulting in superior health and medical care. This includes applications in intensive care as well as diagnostic therapies. The focus is on examples in the use of the promising developments in data science methods, the accumulation of medical and research data. With quality and continuous improvement in process control applications where one determines the usefulness of data analytics, there are great possibilities of change in the improvement in medical applications as well as the management of medical and health-care treatment and diagnostic facilities.

Key Terms: Data analytics; Artificial intelligence; (AI), Autoregressive moving average Modeling; Machine Learning; Multivariate Models; Autocorrelation of Data.

INTRODUCTION

Data analysis and analytics is now everywhere one looks, from the production of most scientifically manufactured component parts to the checkout lines at most supermarkets, hardware stores, and automatic consumer buying via the internet. We refer to this as automation, but it is the advances in computer technologies that drove this mechanization of seemingly simple but technologically advanced tasks to streamline production methodologies. The growth of these technologies in the future will be accelerated by breakthroughs in artificial intelligence (AI), which will continue the mechanization of tasks to improve the quality of output. By including AI into health-care procedures is not simple, but it includes the methodology of statistical and/or mathematical science as it applies to data-driven methodologies. In this study, we focus on one such plan that involves the analytics associated with a volume of diagnostic tests to produce plans to generate treatments.

AUTOMATING THE QUALITY MOVEMENT IN DIAGNOSTICS

Machine learning approaches to problem-solving are growing rapidly within healthcare, Improvements in diagnostic care, whether in hospitals, treatment and diagnostic centers, and other health-care units, are a central function of quality health care. In many places, they are the principal methods by which patients can secure care. The example of Planned Parenthood clinics is one where patients can receive care and treatment in an affordable and often convenient manner for men's health care. Planned Parenthood provides services that often are not available to those who do not have sufficient (or even any) places to obtain affordable care. A client with a severe set of conditions enters the clinic to have scientific tests performed in order to ascertain or determine a diagnosis and therapeutic plan to produce a treatment to successfully reduce the problem and achieve positive results. The process includes a total quality movement (TQM), which is a plan to achieve a successful outcome to the patient's health problem. In the future, we expect machine learning, applications of statistical science, AI and TQM to spread everywhere. Just look at the current research in automobiles and the relative changes made by the driverless vehicle.

To consider the depth of AI and modern data analytics topics in health care, refer to the publications by Jarrett (2008) and (Jarrett and Pan 1981, 2015, 2016). In addition, see Patel et al. (2009), Machado and Costa (2010), Khoo and Quah (2003) and more recently, Acampora et al. (2013) added specific {in addition, Radiol (2019) specified other improvements in 2019 of new computer-based methods. Technology firms such as Google, Amazon, Microsoft, and Apple in recent years made huge investments in AI to deliver tailored search results and build items called personal virtual assistants. The methodology is seeping down to hospital care and other forms of diagnostic and treatment methodology in health care in general. With reforms in health care and health-care reform law, AI will assist physicians and other health-care personnel in choosing medicines and treatments for patients in an efficient and timely manner. For example, a physician who has a patient with a particular diagnosis will be able to choose the best medicine to counter the effect of a severe ailment quickly. With the huge number of medicines available for a physician to prescribe, much decision making will be automated thanks in part to the push for computer systems to prescribe the best treatment available from medical science. No longer will a physician need to peruse volumes of databases to find the optimal treatment. The computer will find and inform health-care personnel to act quickly and optimally.

Today, data collection by health statisticians includes volumes of patient demographic and clinical and billing data, which are in an electronic format for analysis by intelligent software. For these difficult tasks, AI software can analyze quickly to perform the tasks of recommending medicines, treatment protocols, and general advice to assist physicians in attacking the problems associated with difficult diagnoses. For example, applications of AI have been utilized in intensive care for nearly a generation (Hanson and Marshall 2001; Liu and Salinas 2017). In other examples, new digital devices and home tests are allowing a more thorough patient examination remotely, which addresses some of the previous setbacks of telemedicine. Remote diagnostic tools such as perception of telemedicine. Heartbeat and respiration rate can now be checked remotely. The same is true for blood pressure, blood glucose, body temperature, and oxygen levels. A device may contain a high-definition camera that can look down the throat and ear canals. Cameras can also provide high-resolution images of the skin to examine lesions, suspicious skin changes, and other dermatological problems. Urine-testing kits may also be employed in the home or specific diagnostic centers to provide information to medical personnel to suggest a treatment without the patient being in the same physical location as the medical personnel.

At this point, we should consider automated statistical quality control (ASQC) or automated statistical process control (ASPC) as it applies in TQM. These terms are no longer new in diagnostic and treatment terminology; however, they are based on previous applications in industry, banking, and everywhere one seeks assistance in the analysis of data where the timing of decisions is very important. TQM is the field that ensures that management maintains standards set and continually improves the processing of successful goals and achievements. Instead of final, end-of-service inspection (whether the patient is found healthy or not after the treatment ends). TQM according to Lee and Wang (2003) and Weihs and Jessenberger (1999) provides. Instead of end-of-service inspection and decision making, TQM emphasizes prevention, integrated source inspection, process control, and continuous improvement. The mitigating of risks of type I and type II errors are the prime purpose of these methods. In addition, AI will provide software, services, and analytics solutions to the ambulatory care market. In a health-care information technology and services company that delivers the foundational capabilities to organizations that want to promote healthy communities. The technology provides a customizable platform that empowers physician success, enriches the patient care experience, and lowers the cost of health care and, in turn, health insurance. Stated simply, AISQC monitors the incidence characterized by the results of multiple tests on a similar fluid per period of a short interval over a lengthy period (e.g., 10–20 weeks). The monitoring requires an intelligent system analyzing items (e.g., control charts) and seeking whether there are common causes of variation or special causes of variation. In industrial applications, these were called Shewhart charts. Later, others suggested additional methods including the use of exponentially weighted moving average (EWMA) control charts (See Griggs and Spiegelhalter 2007).

The great rise of health information systems enables AI in the very early stages of its development to match one's own intelligence. Computers certainly cannot diagnose like physicians; however, AI software and computer technology are capable of processing vast amounts of data and identifying patterns that humans cannot. AI solves the complex algorithms that analyze these data and is a useful tool to take full advantage of electronic medical records, transforming them from mere e-filing cabinets into full-fledged physician analysts that can deliver clinically relevant, high-quality data in real time.

AISPC AND AISQC IN HEALTH-CARE ENVIRONMENTS

SPC/SQC environments usually assume a steady process behavior where the influence of dynamic behavior does not exist or is ignored. The focus of control is where there is only one variable (e.g., medical test) over a lengthy interval of time. SPC controls for the changes in either the measure of location or dispersion, or both. These procedures as practiced in each phase may disturb the flow of the service production process and operations. We note that in recent years the use of SPC to address processes characterized by more than one test or treatment emerged. First, we review the basic univariate procedures to improve the process of SPC and allow AI to enter the process.

Shewhart control charts were the central foundation of univariate (one variable) SPC, which has a major flaw. The process considers only one piece of data, the last data point, and does not carry the memory of the previous data collected. Often, a small change in the mean of a random variable is not likely to be detected quickly (Griggs and Spiegelhalter 2007). EWMA control charts improved upon the detection process of small process shifts. Rapid detection of relatively small changes in the characteristic of interest and ease of computations through recursive equations are some of the important properties of the EWMA control chart that makes the process attractive and easy to use intelligent software to detect changes.

The EWMA chart is used extensively in time-series modeling where the data contain a gradual drift (Box and Draper 1998). EWMA provides for identifying gradual shifts in medical tests by predicting where the observation will be in the next period of time. Hence, the EWMA process improves decision support in the future and is dynamic (Hunter 1986). The EWMA statistic for monitoring the results of lengthy period of tests having short interval when the actual tests are performed. Furthermore, the method gives less and less weight to data as they become more remote in time. Montgomery's (2013) work contains the development of models for finding control limits in this univariate process but appears to be another example of where intelligent software applies.

ADDITIONAL APPLICATIONS USING UNIVARIATE MODELS

In many applications of univariate analysis, the sample size used in the test process is one. Stated differently, the sample consists of an individual unit the control chart for a sample of one (the individual chart) employs a moving average of two successive observations to estimate the process variability. Obviously, small samples lead to incorrect decisions (stated as an increase in the probability of a type II error) point out problems and issues associated with statistically based evaluations which must be included in intelligent software. A solution may be provided by examining the average run length (ARL) of a proposed solution over a variety of alternative process shifts. ARL performance for an in-control state and for a single shift in a process for which the proposed detection program optimizes must be evaluated. If the system is not optimized, misplaced control limits may result. The system for detection of shifts is sub optimized, and better techniques should be sought. Yeh and Hwang (2004) suggest processes whereby the units are dynamic. In provider-of-care treatments, the distinction between phases I and II of SQC solutions is often not clear. Hence, ARL is often the choice used to assist the providers of care with the assistance they need to recommend courses of treatment.

Alwan (1992) finds that the great majority of SPC applications studied result in control charts with misplaced control limits and essentially false signals to the providers of care. The misplacement results from autocorrelated process observation. The autocorrelated time-series observations violate an assumption associated with Shewhart control charts (Woodall 2005). Autocorrelation of process observations is common in many applications—for example, cast steel (Alwan 2000), wastewater treatment plants (Berthouex et al. 1978), chemical processes many other processes in the health-care industry, especially diagnostic care and similar applications. In addition, suggest using autoregressive integrated moving average (ARIMA) charts for decision analysis. Continuous intelligent software can be of particular aid to identification of the appropriate methods for decision analysis if one follows the works of Atienza et al. (1998), Box et al. (2008), and West et al. (2002) who employed ARIMA modeling with intervention. In addition, Jarrett (2016a, 2016b) summarize many of these method in SPC. All these models are in the process of being computerized to develop intelligent systems that will enable computers intelligently point to optimal patient treatments and diagnoses. The notion of physicians having patient-centered diagnostic programs using AI will be of immense help.

MULTIVARIATE QUALITY CONTROLS (MQC)

Multivariate methods use additional analyses due to having two or more variables that are the results of several diagnostic procedures to determine a specific plan of care (treatment). The use of univariate analysis may lead to incorrect interpretation of data due to the cointegration of the tests performed. The most popular multivariate methods (MQC) are those based on the Hotelling T^2 distribution (West, et al. 2002; Woodall 2005; Yang and Rahim 2005) and multivariate exponential moving average method (MEWMA; Elsayed and Sastri 2007). Other approaches, such as control ellipse, apply for the case of two correlated variables. There are other MQC methods including those developed by Kalagonda and Kulkarni (2003, 2004), Jarrett and Pan (2006, 2007a, 2007b, 2013), Vanhatalo and Kulachi (2015. All the aforementioned MQC modelers produced results that achieve superiority to SQC analysis because of one or more of the following factors:

1. The control region of variables is represented by an ellipse rather than parallel lines.
2. The intelligent software is programmed to maintain a specific probability of a type I error in the analysis.
3. The determination of whether the process is out of control is a single control limit (ARL).
4. By correcting T^2-based MQC analysis, autocorrelation is present. In the data
5. Use of MEWMA, when time-series methods have unique schemes.

As a result, the above methods indicate that intelligent software cannot ignore the various possibilities to lead to non-optimal decisions. However, proper AI methods will adjust to new research, and patient-assisted analytical software will be of great use to find diagnoses that enable one to use AI to solve difficulties with patient care.

LIMITATIONS OF AI, MACHINE LEARNING AND SIMILAR TOPICS

AI, which uses all the methods discussed, is dependent on data science, scientific sample, and statistical analysis. One of the great problems is that AI has yet to come to grips with the huge problems associated with the presently insurmountable problem of language. AI professionals may develop a huge amount of algorithms by combining a small number of mathematical symbols and, in turn, following a small set of rules. Similarly, one can develop an enormous amount of sentences by utilizing a relatively modest number of words and rules. A realistic and useful AI system still needs to cope with the challenges associated with all the possible sentences that may be created in the conversations developed in the AI interrogatory. Genuine AI systems in health care need to have simple and realistic combinations of questions and interpretations that are easily understood and do not require the finite possibility of many interpretations of results. AI will have problems when correct solutions relate to what is “most likely true.” Hence, interrogatories must be tight and simple such that AI cannot rely on insufficient interpretations of questions and answers (see Cambria and White, 2014).

As of this time, the dominant approach to AI is not working out. There is no reason to believe that researchers in AI should return to the projects of making machines actually share some of human’s cognitive abilities. Human cognition could be built into machines applications as there is flexibility in human thought that is goal. Approaching AI has been built into Google Translate and Google Duplex. The limitations of these applications as a form of human intelligence should alert developers. If machine learning and what is entitled “big data” cannot deliver any further than a ticket to a Broadway Show in the hands of the most capable AI firms and developers, it is time to reconsider the strategy associated with AI development.

SUMMARY AND CONCLUSION

The purpose of this study is to encourage growth in a very important industry called artificial intelligence. AI-based platforms for digital transformation will play an increasing role in patient diagnosis health programs. The growth will occur in treatment and emergency care centers as well as intensive care units. Intelligent software is being developed, which will suggest to physicians and other health-care professionals the meaning of studying databases of information data analytics. In turn, intelligent software will prescribe and set protocols for treatments of difficult prognoses and intensive care. Intelligent programs are AI-based platforms for digital transformation. They are modular and an interconnected mixture of flexible digital technologies that span from robotic automation to machine learning. The programs learn over time and produce new ways to arrive at results. The study indicates new ways to get results and in a timely fashion. The blending of intelligent software and comprehensive data analytics will eventually move health-care analysts from the task of interpreting results to have protocols produced for them. Intelligent software will blend seamlessly with a decision maker's operational insights and produce unique domain expertise to create better analytical conclusions in the real world. By examining quality operations, we observe how AI shares the burdens of care and assists health-care personnel in achieving their goals. As stated before, AI in health care incorporates AI into many health-care procedures that are not simple, but includes the methodology of statistical/ mathematical science as it applies the data-driven methodologies.

References

Acampora, G., Cook, D.J., Rashidi, P., and Vasilakos, A.V. (2013). "A Survey on Ambient Intelligence in Healthcare." *Proceedings of the IEEE*, 101, 2470–2494. Doi: 10.1109/JPROC.2013.2262913.

Alwan, L.C. (1992). "Time-Series Investigation of Subsample Mean Charts." *Communications in Statistics—Theory and Methods*, 21 (4), 1025–1049.

Alwan, L.C. (2000). *Statistical Process Control*. New York: Irwin-McGraw-Hill.

Atienza, O.O., Tang, L.C., and Ang, B.W. (1998). "A SPC Procedure for Detecting Level Shifts of Autocorrelated Processes." *Journal of Quality Technology*, 30, 340–351.

Berthouex, P.M., Hunter, E., and Pallesen, I. (1978). "Monitoring Sewage Treatment Plants, Some Quality Control Aspects." *Journal of Quality Technology*, 10 (4), 149–159

Box, G.E.P., and Draper, N.R. (1998). *Empirical Model Building and Response Surfaces*. New York: Wiley.

Box, G.E.P., Jenkins, G.M., and Reinsel, G.C. (2008). *Time Series Analysis, Forecasting and Control*, 4th Ed. New York: Wiley.

Cambria, E., and White, B. (2014). "Jumping NLP Curves: A Review of Natural Language Processing Research [Review Article]." *IEEE Computational Intelligence Magazine*, 9 (2), 48–57. doi: 10.1109/MCI.2014.2307227.

Elsayed, E.A., and Sastri, T. (2007). "Design of Optimum Simple Step-Stress Accelerated Life Testing Plans." *Recent Advancement of Stochastic Operations Research*, edited by S. Dohl, T.S. Osaki, and K. Sawaki. Singapore: World Scientific.

Griggs, O.A., and Spiegalhalter, D.J. (2007). "A Simple Risk-Adjusted Exponentially Weighted Moving Average." *Journal of the American Statistical Association*, 102 (477), 140–152.

Hanson, C., and Marshall, B. (2001). "Artificial Intelligence Applications in the Intensive Care Unit." *Critical Care Medicine*, 29 (2), 427–435.

Jarrett, J.E. (2016a). “Total Quality Management (TQM) Movement in Public Health.” *International Journal of Quality & Reliability*, 33 (1), 25–41. Doi: 10.1108/IJQRM-12-2013-0193.

Jarrett, J.E. (2016b). “Data Analytics and Managing Health and Medical Care.” *Global Journal of Human Social Sciences*, 16 (4), 17–24.

Jarrett, J.E., and Pan, X. (2006). “The Quality Control Chart for Monitoring Multivariate Autocorrelated Processes.” *Computational Statistics and Data Analysis*, 51, 38621–38700.

Jarrett, J.E., and Pan, X. (2007a). “Using Vector Autoregressive Residuals to Monitor Multivariate Processes in the Presence of Serial.” *International Journal of Production Economics*, 106, 204–216.

Jarrett, J.E., and Pan, X. (2007b). “Monitoring Variability and Analyzing Multivariate Processes.” *Journal of Applied Statistics*, 34 (4), 459–469.

Jarrett, J.E., and Pan, X. (2013). “Constructing SPC Charts by Cumulative Square and Cumulative Variance Methodologies.” *International Journal of Management and Industrial Engineering*, 3 (6), 247–253.

Jarrett, J.E., and Pan, X. (2015). “The Multivariate EWMA Model and Monitoring Bio Surveillance.” *International Journal of Advances in Management, Economics and Entrepreneurship*, 2 (12), 1–6.

Kalagonda, A.A., and Kulkarni, S.R. (2003). “Diagnoses of Multivariate Control Chart Signal for Autocorrelated Processes.” *Communications in Statistics—Theory and Methods*, 14 (110), 2657–2688.

Kalagonda, A.A., and Kulkarni, S.R. (2004). “Multivariate Quality Control for Autocorrelated Processes.” *Journal of Applied Statistics*, 31 (3), 317–327.

Khoo, M.B.C., and Quah, S.H. (2003). “Incorporating Runs Rules into Hotelling’s χ^2 Control Charts.” *Quality Engineering*, 15 (4), 671–675.

Lee, H.L., and Wang, S. (2003). “Higher Supply Chain Security and Lower Cost Lessons from Total Quality Management.” Research Paper No. 1824, Stanford Graduate School of Business, Palo Alto, CA.

Liu, N.T., and Salinas, J. (2017). “Machine Learning for Predicting Outcomes in Trauma.” *Shock*, 48 (5), 504–510. Doi: 10.1097/SHK.0000000000000898.

Marques, I., Captivo, M.E., and Vaz Pato, M. (2014). “Scheduling Elective Surgeries in a Portuguese Hospital Using a Genetic Heuristic.” *Operations Research in Health Care*, 3 (2), 59–72.

Montgomery, D.C. (2013). *Introduction to Statistical Quality Control*, 7th Ed. New York: Wiley.

Montgomery, D.C., and Mastrangelo, G.C. (1991). “Statistical Quality Control in a Computer-Integrated Manufacturing Environment.” *Statistical Process Control in Automated Manufacturing*, edited by J. Kates and N. Hunele. New York: Marcel Decker.

Patel, V.L., Shortliffe, E.H, Stefanelli, M., Szolovits, P., Berthold, M.R., Bellazzi, R., and Abu-Hanna, A. (2009). “Coming of Age of Artificial Intelligence in Medicine.” *Artificial Intelligence in Medicine*, 46 (1), 5–17.

Radiol. 2019 Aug; 92(1100): 20190001. Published online 2019 Jun 3. Doi: 10.1259/bjr.20190001

Vanhatalo, E., and Kulachi, M. (2015). “The Effect of Autocorrelation on the Hotelling T^2 Control Chart.” *Quality and Reliability Engineering International*, 31 (8), 1779–1796.

Weihs, C., and Jessenberger, J. (1999). “Statistische Methoden zur Qualitætssicherungen und Optimierungen.” *Statistica Neerlandica*, 48, 147–168.

West, D., Dellana, S., and Jarrett, J.E. (2002). “Transfer Function Modeling with Dynamic Inputs.” *Journal of Quality Technology*, 34 (3), 315–326.

Woodall, W.H. (2005). “The Use of Control-Charts in Health Care Public Health Surveillance.” *Journal of Quality Technology*, 38 (2), 89–104.

Yang, S.F., and Rahim, R.A. (2005). “Economics Statistical Process Control for Multivariate Quality Characteristics under Weibel Shock Model.” *International Jordan of Production Economics*, 98, 215–226.

Yeh, A.B., Hwang, L., and Wu, Y. (2004). “A Likelihood-Ratio-Based EWMA Chart for Monitoring Variability of Multivariate Normal Processes.” *IIE Transactions*, 36, 863–879.