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Applications of advanced analytics in healthcare

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ABSTRACT

Analytics is increasingly becoming a key tool to support informed management decisions in organisations. An organisation's capability to make use of data analytics can enhance efficiencies and increase competitive differentiation and advantage. In the context of healthcare, analytics can support improved health outcomes and hence stakeholder value that enhances affordability and access to care. A deep understanding of analytics applications and techniques lends itself to identification of opportunities where analytics techniques are best applied. This paper introduces analytics maturity models as a tool to inform proportionally appropriate analytics applications. In this paper, a broader perspective is provided through consideration of the position on the analytics maturity curve of current techniques utilised in the healthcare system. The relationship between analytics maturity and analytics techniques in the healthcare space is then explored to demonstrate that there are opportunities for applying more sophisticated techniques to more advanced applications and hence enhance the efficiency of healthcare outcomes and health risk management

KEYWORDS

Healthcare, advanced analytics, health economics, South Africa, Africa

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1. INTRODUCTION

1.1 Analytics is increasingly being used as a tool to support informed management decision-making (Ghasemaghaei et al., 2018). Terms such as 'advanced analytics', 'machine learning' and 'artificial intelligence' tend to be used interchangeably to describe the use of large datasets to support decision-making (Watson, 2017). The distinction between analytics applications and analytics techniques utilised is often not well understood in industry (Watson, 2017). This paper aims to clarify the difference between analytics applications (the problem statement) and analytics techniques (the methodology used to determine a result). A deep understanding of analytics applications and techniques lends itself to identification of optimal instances where these techniques are best applied.

1.2 Effective use of analytics is important in the healthcare industry which is characterised by large volumes of data in the case of health insurance applications and the need to extrapolate sampling results in the case of health research applications (Barton & Court, 2012).

1.3 Maturity models are used to evaluate the extent to which business decisions are made making use of analytics techniques and the relative associated complexity thereof (Król & Zdonek, 2020).

1.4 In Section 2, analytics applications will be discussed in the context of various maturity models. The similarities and differences between these maturity models will be explored. Section 3 discusses various advanced analytics techniques and reviews the evolution of advanced analytics towards data driven decision-making in organisations which are on the mature end of the analytics maturity continuum.

1.5 Section 4 highlights the application of analytics in the healthcare industry in order to assess the current manner in which analytics techniques are used to inform strategic decision-making in healthcare. Analytics examples found in healthcare are categorised into the maturity framework and analytics techniques set out in Sections 2 and 3 to potentially identify areas in healthcare where analytics adoption can be improved.

2. ANALYTICS APPLICATIONS: MATURITY MODELS

2.1 Organisations utilise data to various extents to inform decision-making geared towards increasing competitive advantage or operational efficiencies (Król & Zdonek, 2020). An organisation's capability to make use of data analytics can be defined by the degree of the organisation's analytics maturity (ibid.).

2.2 Competitive advantage is best defined as an organisation's ability to implement its strategy through the organisational vision, appropriate use of resources and capabilities, realising innovation and quality in products and services or manufacturing at lower production costs than competitors (Hameed, 2019). Porter (1989) states: "competitive advantage grows fundamentally out of value a firm is able to create for its buyers that exceeds the firm's cost of creating it. Value is what buyers are willing to pay, and superior value stems from offering lower prices than competitors for equivalent benefits or providing unique benefits that more than offset a higher price."

2.3 In the healthcare context specifically, increased operational efficiencies will result in improved quality of care to a patient in the healthcare system (Yoon et al., 2016).

2.4 Analytics maturity can therefore be defined as the placement on an analytics continuum describing the extent to which an organisation acts on data (Król & Zdonek, 2020). Król & Zdonek (2020) and Menezes et al. (2019) categorise analytics maturity into five categories:
— **Descriptive analytics** – understanding the observed history through pattern identification: What happened?
— **Diagnostic analytics** – detection of relationships (correlations) between variables: Why did it happen?
— **Predictive analytics** – forecasting future expected scenarios: What may happen in future?
— **Prescriptive analytics** – modelling and simulation to suggest actions to be taken in order to make better decisions: What actions should be taken?
— **Cognitive analytics** – monitoring the relationship between action taken and outcome in real time to inform future optimal actions.

2.5 Król & Zdonek (2020) note further that in practice analytics maturity categories co-exist and complement each other. For this reason, analytics maturity is assessed considering a continuum. Menezes et al. (2019) support this approach stating there are often overlapping areas in the use of analytics in business. Shmueli & Koppius (2011) suggest that explanatory (descriptive and diagnostic) versus predictive (predictive, prescriptive and cognitive) approaches address two distinct goals i.e. analysing versus forecasting. Cao & Duan (2017) utilise eight categories to describe analytics: reporting, statistical analysis, alerting, forecasting, predictive modelling, optimisation, prescriptive analytics and actionable knowledge delivery. Reporting, statistical analysis, alerting and forecasting are grouped together as explicit analytics (which aligns to descriptive and diagnostic analytics in paragraph 2.4); predictive modelling, optimisation, prescriptive analytics and actionable knowledge delivery categorisations align to the definitions put forward by Król & Zdonek (2020) and Menezes et al. (2019).

2.6 The analytics maturity path therefore shows an organisation's analytics maturity stages beginning from the application of descriptive analytics (least mature) and ending with cognitive analytics (most mature).

2.7 For purposes of this paper, we will refer to the five stages outlined in paragraph 2.4 noting that nuances exist in the distinct analytics maturity categories as seen by the difference in the categories provided by Cao & Duan (2017) and Shmueli & Koppius (2011). However, the five categories in paragraph 2.4 are widely accepted as distinct categories in the analytics continuum.

2.8 It is important to note that the evolution of the use of analytics in an organisation is not necessarily uniformly distributed. The implementation of organisational changes may vary in terms of the order and intensity, depending on both an organisation's specific characteristics and the broader external business context (Król & Zdonek, 2020; Menezes et al., 2019; Sun & Huo, 2019).

2.9 Assessing an organisation's analytics maturity across the analytics continuum can be conducted through various analytics maturity models discussed by various authors (Król & Zdonek, 2020; Lismont et al., 2017). Some of these models are discussed below.

2.10 Analytics maturity continuum

2.10.1 Analytics maturity can be described as the evolution of an organisation to integrate, manage, and leverage all relevant internal and external data sources into key decision points (Król & Zdonek, 2020). Barton & Court (2012) assert the importance of analytics maturity, calling it an increasingly important point of competitive differentiation. Competitive differentiation (a subset of competitive advantage as defined in paragraph 2.2) is defined as: an organisation outperforming a competitor in certain aspects of product design such that it experiences reduced sensitivity to sales volumes for other product-design related features (Dirisu et al., 2013). Barton & Court (2012) highlight that while the importance of advanced analytics is generally accepted by executives and senior management, most organisations are unclear on how to reach advanced levels on the analytics spectrum (ibid). Maturity models are used to guide a transformation process from rudimentary levels of analytics maturity to more advanced levels (Król & Zdonek, 2020). Once analytics maturity has been assessed and gaps have been identified, a roadmap can be developed to improve the analytics maturity of an organisation or industry (Barton & Court, 2012).

2.10.2 Most businesses have considerable experience in the use of descriptive and diagnostic analytics (Król & Zdonek, 2020) and research of analytics adoptions indicates that many organisations are still in the initial stages of the analytics maturity path (Lismont et al., 2017). These organisations are aiming to move to more advanced analytics that may increase the effectiveness of the actions they take (Król & Zdonek, 2020). Forecasts and simulations are examples of predictive, prescriptive, and cognitive analytics applications, resulting in optimised outcomes (Barton & Court, 2012).

2.10.3 An assessment of an organisation's analytics maturity can be carried out in a variety of ways (Lismont et al., 2017). Traditional methods of measuring analytics capacities include self-assessment, qualitative interviews, and quantitative studies (Król & Zdonek, 2020). However, a traditional approach to the assessment of analytics capacities has certain limitations, mainly due to the lack of an opportunity to verify them (ibid.). Self-assessment and quantitative studies are usually carried out using a checklist to determine whether specific technologies and analytics tools have been implemented (ibid.). At the same time, however, they do not enable an assessment as to whether an organisation fully uses these tools to support business decisions, and whether they affect the organisation's activities (ibid). An alternative to these methods is studies carried out using analytics maturity models (ibid.).

2.10.4 Maturity models have been designed to assess the analytics maturity of an organisation (Król & Zdonek, 2020). The maturity model serves as the scale for the appraisal of the position on the evolution path (Lismont et al., 2017). It provides criteria and characteristics that need to be fulfilled to reach a maturity level (ibid). During a maturity appraisal, a snapshot of the organisation regarding the given criteria is made (ibid).

2.10.5 Król & Zdonek (2020) provide an overview of eleven different types of analytics maturity models. The analytics models were selected based on an extensive review of scientific literature: Davenport et al. (2010) developed the DELTA model; Hamel (2019) developed the Web Analytics Maturity Model; Blast Analytics and Marketing developed the Blast Analytics Maturity Assessment Framework[1] based on the Web Analytics Maturity Model developed by Hamel (2019); Halper & Stodder (2014) developed the TDWI Analytics Maturity Model; Association Analytics developed the Data Analytics Maturity Model for Associations;[2] Gartner developed Gartner's Maturity Model for Data and Analytics;[3] and SAS Institute developed the SAS Analytics Maturity Scorecard.[4]

2.10.6 Lismont et al. (2017) discuss five authors' approaches to analytics maturity models. This includes the models proposed by Saxena & Srinivasan (2013), Cosic et al. (2012), Comuzzi & Patel (2016), LaValle et al. (2011) and Ransbotham (2015).

2.10.7 Most of the models described in the literature aim to classify the stages of analytics maturity and are based on interpretation of survey and interview research to assess data warehousing and business intelligence (Lismont et al., 2017). Analytics maturity models thus provide frameworks to place an organisation on the analytics maturity curve (ibid.)

2.10.8 Figure 1 illustrates the analytics maturity continuum visually, as understood by the authors.

3. ADVANCED ANALYTICS TECHNIQUES

3.1 Advanced analytics is likely to become a decisive competitive asset in many industries and a core element in companies' efforts to improve performance (Barton & Court, 2012). Section 2 discussed analytics maturity models and how these are used to determine analytics adoption across various industries. A deep understanding of the problem being addressed as well as the techniques being utilised is necessary in order to solve problems in a manner that aligns with materiality and proportionality actuarial principles. The principle of materiality refers to the concept that an omission, understatement, or overstatement is material if the actuary expects it to affect either the user's decision-making or the user's

1 https://www.blastanalytics.com/analytics-maturity-assessment
2 https://associationanalytics.com/2017/12/29/5-areas-assess-data-analytics-maturity-model/
3 https://www.gartner.com/en/newsroom/press-releases/2018-02-05-gartner-survey-shows-organizations-are-slow-to-advance-in-data-and-analytics
4 https://www.sas.com/pl_pl/whitepapers/five-steps-to-analytical-maturity-106929.html

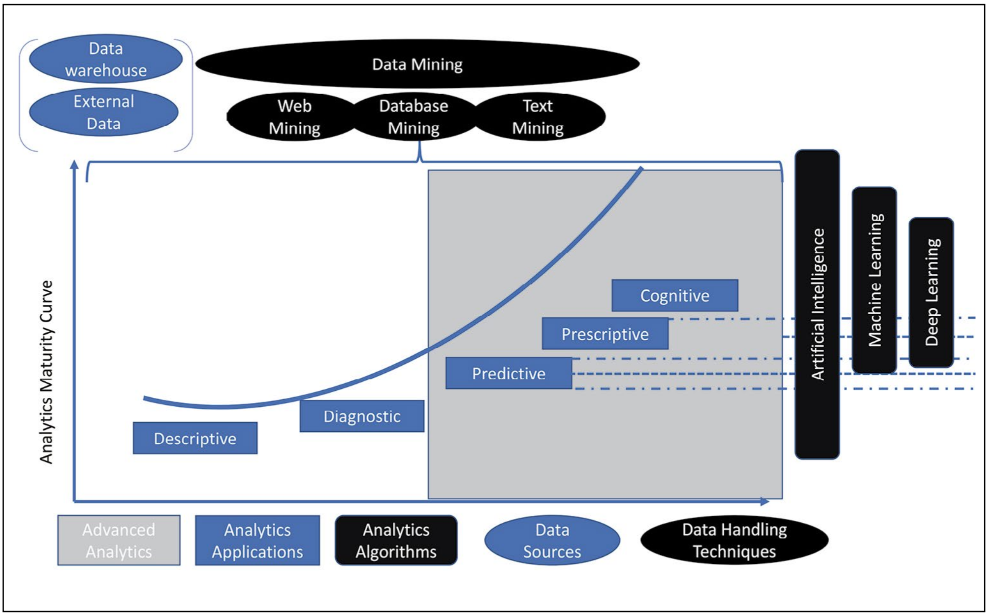

FIGURE 1. Analytics maturity continuum. Source: Authors

reasonable expectations and is generally considered amongst the actuarial community to be based on judgement (Herbers, 2002). On the other hand, proportionality principles consider that variables should be considered in comparison to the proportional impact on the overall result (Van Hulle, 2014). This section discusses the various techniques utilised across various industries to solve business challenges.

3.2 Advanced analytics is a general term which simply means applying various analytics techniques to data to answer questions or solve problems (Bose, 2008). Advanced analytics is not a tool or technology, but rather, a group of techniques that are used in combination with one another to gain information, analyse that information, and determine potential outcomes (ibid.).

3.3 This section explores commonly utilised mechanisms for data generation and commonly utilised analytics techniques: artificial intelligence, machine learning and deep learning.

3.4 Data integration and data mining

3.4.1 Data integration and data mining are the basis for analytics. The more information gathered and integrated, the easier pattern recognition and relationship identification will be (Bose, 2008). Current advanced analytics applications increasingly use data integration and data mining techniques to prepare data (Sparks et al., 2016). Various artificial intelligence, machine learning and deep learning techniques can be utilised for data mining (Mitchell, 1997); these techniques are explored in detail below.

3.4.2 Data mining is a powerful technique for the automatic extraction of patterns, associations, changes, anomalies and significant structures from data (Bose, 2008). These uncovered patterns from data play a critical role in decision-making because they reveal areas for process improvement (Mitchell, 1997; Bose, 2008). Most of the value of data mining comes from using data-mining algorithms to improve the accuracy of analytics applications through enhancing understanding of the data and assisting with identification of areas for process improvement (ibid.).

3.4.3 Text mining and web mining are examples of data mining that have enabled the use of analytics to improve organisational performance through analysing unstructured customer data in the form of textual comments from survey research, e-mails and log files from web servers, which were previously unusable (Bose, 2008).

3.4.4 Sun & Huo (2019) define the relations among deep learning, machine learning, and artificial intelligence, which are mathematically represented as follows:

$$\text{deep learning} \subset \text{machine learning} \subset \text{artificial intelligence.}$$

That is, deep learning is a proper subset of machine learning, and machine learning is a proper subset of artificial intelligence (Russell & Norvig, 2010; Wu et al., 2019). This is expanded on in the sections that follow in order of increasing complexity.

3.5 Artificial intelligence

3.5.1 Artificial intelligence (AI) traditionally refers to an artificial creation of human-like intelligence that can learn, reason, plan, perceive, or process natural language (Dick, 2019). AI is considered to be a subset of computer science, focused on providing computers with the sophistication to act intelligently (Nilsson,1982).

3.5.2 AI can therefore be defined as the universe of computing technology that exhibits anything remotely resembling human intelligence (Dick, 2019). AI systems can include anything from a problem-solving application that makes decisions based on complex rules (if/then logic) to a computer that develops the intelligence, free will, and emotions of a human being (Dick, 2019). Nilsson (1982) similarly defines AI techniques, namely: heuristic search, decision trees, game theory, rule-based deductive systems and object-oriented representations.

3.5.3 Artificial intelligence is further categorised into 'narrow AI' or 'general AI'. Narrow AI is designed to perform specific tasks within a domain (e.g. real-time estimation of a mobile agent's location using hidden Markov models (Beaulac & Larribe, 2017). General AI is hypothetical and not domain specific but can learn and perform tasks anywhere to achieve true human-like intelligence (Lieto et al., 2018). All AI applications observed today are examples of narrow AI as we have not mastered replication of true human-like intelligence to date (Bundy, 2017).

3.6 Machine learning

3.6.1 Machine learning is a subset of AI application that improves through experience (Jordan & Mitchell, 2015). It reprogrammes itself, as it digests more data, to perform the specific task its designed to perform with increasingly greater accuracy (ibid.).

3.6.2 Rätsch (2004) explains machine learning uses pattern recognition; the modeller attempts to build algorithms capable of automatically constructing methods for distinguishing between different examples based on differentiating patterns. Examples given are: human faces, text documents, handwritten letters or documents, and the DNA sequences that cause certain diseases.

3.6.3 Analytics uses artificial intelligence and machine learning to build algorithms in order to extract knowledge through existing data, combine them and, as a result, forecast the future (Lopes et al., 2020). Mitchell (1997) explains machine learning is best understood in context of its role within computer science; examples include difficult-to-programme applications through rule-based logic which highlight the need for machine learning (e.g. facial recognition) and those which do not due to their simplistic and easily programmable underlying rule-based logic (e.g. matrix multiplication). These algorithms can be divided into two main categories: unsupervised and supervised learning.

3.6.4 Unsupervised learning is mostly known for characteristic extraction which can be very useful in different types of analysis as it will automatically identify structure in data (Lopes et al., 2020). The major unsupervised learning method is clustering, a process of grouping similar entities. The goal is to find similarities in the data and to group similar data points together (ibid.).

3.6.5 Supervised learning is typically done in the context of classification when input to output labels are mapped, or regression when input to a continuous output is mapped (ibid.). Supervised learning is used in healthcare to determine better clinical outcomes (Lopes et al., 2020). It includes use of techniques such as: linear regression, logistic regression, naive bayes, decision trees, nearest neighbour, random forests, support vector machine and neural network applications (ibid.).

3.6.6 Unsupervised learning can be used as part of the pre-processing step to reduce dimensionality or identify subgroups, summarising and explaining data features, making a significant contribution to the results. This can then lead to the application of supervised learning techniques. Supervised learning enhances the efficiency, both of processing and of the desired results, according to the objectives and the type of existing data (ibid.). To illustrate this difference, Maitland (2002) discusses the unsupervised technique of principal-components analysis which explains the variance-covariance structure of the original variables. Construction of principal components then assists with identifying subgroups in the data in order to make the modelling process easier due to the reduction in the size of the dataset. Reducing the number of variables of a dataset naturally comes at the expense of accuracy, but the trick in dimensionality reduction is to trade a little accuracy for the ability to process data and provide results more quickly. Smaller datasets are easier to explore and visualise and make analysing data much easier and faster for machine learning algorithms without extraneous variables to process (Wold et al., 1987).

3.6.7 More recently, semi-supervised learning has been introduced as a hybrid between unsupervised and supervised learning. The semi-supervised learning algorithm is trained upon a combination of labelled and unlabelled data and is suitable for scenarios where there is a lack of results in certain contexts (Lopes et al., 2020). Semi-supervised learning is currently being used in a range of smart healthcare applications (Zahin et al., 2019).

3.7 Deep learning

3.7.1 Deep learning, in its simplest form, consists of artificial neural networks with many hidden layers, allowing the models to discover intricate structure in large datasets (Smith et al., 2016).

3.7.2 Since 2006, deep learning has been increasing in popularity (ibid.). Several factors have contributed to this revival. Unsupervised methods have been used to pre-train the networks, improving the feasibility of feature detection; and graphical processing units have been used to train the networks, making training of large networks possible (ibid.).

3.7.3 Deep learning is a subset of machine learning originating from artificial neural networks, in which feedforward neural networks are combined with many hidden layers of logic (Zhang et al., 2017).

3.7.4 Figure 2 illustrates the relationship between artificial intelligence, machine learning and deep learning as defined by Sun & Huo (2019), illustrated by the authors.

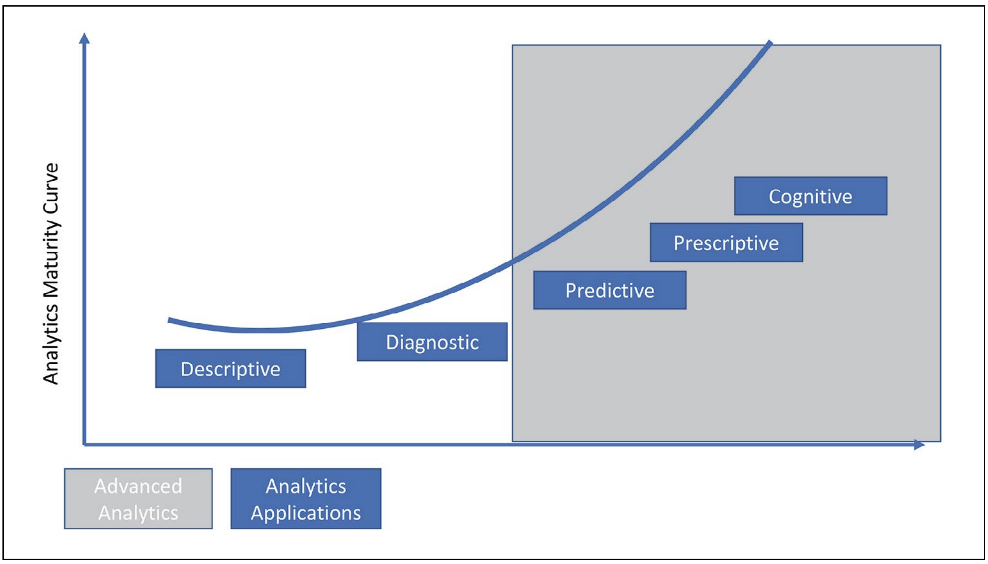

FIGURE 2. Relationship between artificial intelligence, machine learning and deep learning (Authors' reflection of definitions by Sun & Huo, 2019)

4. APPLICATIONS OF ADVANCED ANALYTICS IN HEALTHCARE

4.1 Various models to assess analytics maturity exist and have been outlined in Section 2. The purpose of any analytics maturity model is to assist with gap identification in the application of analytics (Król & Zdonek, 2020). As discussed by Lismont et al. (2017) and Król & Zdonek (2020) in paragraph 2.10.3, one method for assessing an organisation's maturity is through qualitative research. Since the aim is to understand how a community or individuals within it perceive the extent of the application of analytics, qualitative methods are often appropriate (McCusker & Gunaydin, 2015).

4.2 This section considers advanced analytics applications in the healthcare space and, in this context, an analogy between the 'organisation' referred to by Król & Zdonek (2020) and the 'healthcare system' can be drawn. Islam et al. (2018) conducted a qualitative literature review and examined analytics in two areas, namely clinical and administrative decision-making. In this paper, a broader perspective is provided through inclusion of additional healthcare system components, categorised by the authors, which include: patient experience, patient behaviour, medical treatment (diagnosis, lab and radiology), healthcare resource allocation, billing, disease modelling and health economics. These disciplines appeared as common themes in the literature review. Utilising these disciplines, this research examines analytics in broader healthcare disciplines while categorising each application according to the placement on the analytics maturity curve and the sophistication of the analytics technique utilised. The relationship between analytics maturity and analytics techniques in the healthcare space is then explored.

4.3 Health economics

4.3.1 Choi et al. (2016) introduce health economics as one of the main emerging fields of economics. They further discuss the potential of using a combined analytics and health economics approach to propose a mutually beneficial public-private partnership healthcare system.

4.3.2 Rawlins et al. (2010) discuss the key role health economics currently plays in cost-benefit, cost-effectiveness, cost-minimisation, cost-of-illness and cost-utility analyses. Rawlins et al. (2010) further describe the cost-effectiveness measure as being the industry preferred method to inform health economics-based decision-making. Cost-effectiveness measures make use of economic modelling of quality adjusted life years (QALYs) (ibid.). This is supported by Marshall et al. (2015) who state that typically traditional economic modelling methods are used to conduct health economic analyses.

4.4 Medical treatment (including diagnosis)

4.4.1 Stochastic trees have been utilised to enhance the decision-making process in medical treatment procedures (Kudyba & Gregorio, 2010).

4.4.2 Data mining of laboratory tests and radiology examinations provides vital information for physicians to administer corresponding treatment plans, where breakdowns or inhibitors of these processes can adversely affect timely treatment activities which are depicted in corresponding outcome metrics (Kudyba & Gregorio, 2010).

4.4.3 Lopes et al. (2020) discuss analytics applications utilised to detect cancer at an earlier stage, based on genetic and non-genetic factors. In a recent study, a hybrid system was developed with data-mining algorithms, to build a predictive model capable of distinguishing between breast cancer and non-breast cancer diagnoses with 100% accuracy (ibid.). Lopes et al. (2020) also discuss a study conducted in Taiwan by a team of researchers who utilised data-mining techniques based on logistic regression to predict the survival rate among oral cancer patients, with 95.7% accuracy.

4.4.4 Other studies utilising similar techniques to diagnose leukaemia patients and improve accuracy of early detection of heart disease are also outlined (ibid.). Applications of analytics in each study varied, including analysis of multiple risk factors to predict the likelihood of disease positivity and the generation of scorecards to determine the likelihood of certain outcomes.

4.4.5 Wesdorp et al. (2021) conducted a review on the value of radiomics in predicting response to treatment in patients with gastrointestinal tumours. The review found radiomics has great potential to predict patient response to treatment and therefore improve patient selection and early adjustment of treatment strategy in a non-invasive manner (ibid.).

4.5 Healthcare resource allocation

4.5.1 Raghupathi & Raghupathi (2014) conducted a literature review on analytics applications and their potential in the healthcare space. Their findings identify hospital management processes (including healthcare practitioner allocation) to be a primary area where analytics can be applied to improve efficacy.

4.5.2 Operational efficiency for healthcare organisations refers to more accurately identifying where resources are required and how to allocate resources effectively to meet arising demand. Resources in this context include financial, human and treatment resources (Kudyba & Gregorio, 2010).

4.5.3 David et al. (2019) studied a commercial insurer-driven intervention to improve resource allocation. This was structured as a claims-based algorithm to determine a member level healthcare utilisation risk score in order to identify members most likely to benefit from care management teams. Focusing resources on those with predicted greater need leads to improved outcomes for the same level of resource input as compared to a less focussed approach.

4.6 Patient experience

4.6.1 Kudyba & Gregorio (2010) discuss a case study approach to illustrate the effectiveness of the neural network analytic method to identify factors within the patient treatment process that produce high variances in performance metrics; factors included supply chains and patient flow management (ibid.).

4.6.2 Yeh et al. (2016) explore the potential of radiologists utilising social media platforms to engage with patients. Specific focus is given to current examples of physicians using of mineable social media content (an example of web mining) to provide patient-centred communication and information exchange to improve the overall patient experience (ibid.).

4.6.3 Ranard et al. (2016) explain how Yelp reviews of hospital care are being utilised to supplement and inform traditional surveys of the patient experience. Yelp is defined as a popular American real-time online rating platform and as at 2016 Yelp was the most widely used freely available commercial website in the United States for hospital ratings (ibid.). Natural language processing is used to conduct text mining of all Yelp narrative reviews to provide segmented underlying topics (ibid.).

4.6.4 Understanding patient experience is important for improving healthcare outcomes since improved experience is associated with greater compliance with treatment as well as driving overall healthcare system transformation (Browne et al., 2010)

4.7 Patient behaviour

4.7.1 In healthcare, data analytics have been used to predict which characteristics of people are associated with noncompliance with healthcare treatment procedures, allowing for more personalised interventions (Kudyba & Gregorio, 2010). Kankanhalli et al. (2016) state that it is possible to determine patient behaviour and sentiment from wearable devices, social media posts and web pages. Rose & Burgin (2014) similarly discuss monitoring of patient behaviour as a mechanism to manage healthcare delivery costs through administration and delivery (Hermon & Williams, 2014). Kudyba & Gregorio (2010) add that contextualised patient behaviour information and preventive suggestions can be made available to patients by associating personal data with locations, health indicators and weather conditions.

4.7.2 Krishnan et al. (2015) found that it is possible to change patient behaviour using strategies such as phone reminders and educational programmes to influence factors such as the rate of non-attendance of follow-up treatment. Strategies taken were informed by various regression models.

4.7.3 Vry et al. (2016) explore using cross-sectional patient experience survey data to identify healthcare-seeking behaviour. Patient characteristics were used as independent variables for regression analyses (ibid.). The study determined patient characteristic differences influencing healthcare-seeking behaviour (ibid.). Vry et al. (2016) further assert that the research can be used to improve barriers to healthcare access by identifying individuals in need of prompting to seek timely healthcare services.

4.8 Financial management

4.8.1 Data-mining techniques enable decision-makers to identify patterns in clinical-, claims- and activity-based historical data, to better identify and understand explanatory relationships between variables that describe operational processes (Kudyba & Gregorio, 2010).

4.8.2 Branting et al. (2016) present a novel approach to utilising analytics, specifically: network algorithms to identify healthcare fraud risk in insurance pools. The algorithms considered included: calculation of behavioural similarity to known fraudulent and non-fraudulent healthcare providers with respect to measurable healthcare activities; and estimation of likelihood of fraud using geospatial analysis on shared practice locations and other addresses (ibid.).

4.8.3 Mehta & Pandit (2018) and Raghupathi & Raghupathi (2014) highlight claims data as a central source of healthcare data, explaining healthcare data sources are disorganised and fragmented having different structures and forms. Mehta & Pandit (2018) discuss the need for all data sources to be integrated to provide a holistic view of the patient. Specific focus is given to the use of holistic patient data to improve health-process efficiency and reduction of healthcare costs through improved documenting and reporting (ibid.)

4.8.4 Similarly, Chen et al. (2020) discuss the integral role analysis of claims information plays in assisting with reducing administrative costs and decreasing fraud, waste, and abuse. The applications of analytics in financial management of healthcare insurance risk pools is critical for preserving financial integrity and sustainability and hence promoting access to healthcare cover.

4.9 Disease modelling

4.9.1 Reddy et al. (2011) utilise advanced analytics to facilitate an understanding of HIV progression and highlight the factors that influence disease progression. This work can be used to develop new treatment strategies.

4.9.2 Barry et al. (2018) explore the current state of the field of outbreak analytics—defined as an emerging area of data science focused on the technological and methodological aspects of the outbreak data pipeline. Barry et al. (2018) discuss current approaches to disease modelling, particularly in the context of a pandemic. This includes database design and mobile technology, frequentist statistics and maximum-likelihood estimation, interactive data visualisation, geo-statistics, graph theory, Bayesian statistics, mathematical modelling, genetic analyses and evidence synthesis approaches.

4.9.3 Giordano et al. (2020) similarly discuss use of the multistate susceptible-infected-removed (SIR) model (a predictive mathematical model for epidemics) as being fundamental to understanding the course of the Covid-19 pandemic and therefore enabling planning of appropriate control strategies. These models have been constructed at rapid pace from various data sets which are both structured and unstructured.

4.9.4 These are some notable examples from the literature illustrating that analytics applications are present and highly utilised in healthcare and are rapidly becoming an indispensable tool for clinicians and risk managers in ensuring interventions are appropriate and effective in improving health outcomes. However, while there is research evidence supporting use of these techniques, what is not addressed is the relationship between the sophistication of the application and the sophistication of the technique as described in the current literature. This paper addresses this gap by examining this relationship and illustrating diagrammatically the difference between analytics applications and analytics techniques. Through understanding of these terms this paper highlights the need to use principles of materiality and proportionality when utilising analytics to support decision-making.

5. KEY FINDINGS

5.1 Table 1 summarises the various applications and techniques in industry as categorised by the authors.

TABLE 1. Summary of literature review classified integrating analytics maturity and analytics technique frameworks

Discipline	Use case	Application	Technique	Reference
Patient experience	Optimal patient pathway: neural network	Cognitive	Artificial intelligence	Kudyba & Gregorio (2010)
	Patient care: context-sensitive decision support	Unknown	Unknown	Yeh et al. (2014)
	Patient centred communication: Web mining social media content	Descriptive	Artificial intelligence	Ranard et al. (2016)
	Hospital care process improvement	Descriptive	Machine learning	Browne et al. (2010)
Patient behaviour	Determine characteristics of patients associated with noncompliance	Diagnostic	Machine learning	Kudyba & Gregorio (2010)
	Determine patient behaviour and sentiment	Diagnostic	Machine learning	Kankanhalli et al. (2016)
	Monitoring patient behaviour to manage healthcare claims costs	Diagnostic	Machine learning	Rose & Burgin (2014)
	Changing patient behaviour	Predictive	Machine learning	Krishnan et al. (2015)
	Understanding health-seeking patient behaviour	Predictive	Artificial intelligence	Vry et al. (2016)
Medical treatment	Treatment procedure: stochastic trees	Cognitive	Artificial intelligence	Kudyba & Gregorio (2010)
	Lab tests: rule-based logic on outcomes	Diagnostic	Not disclosed	Kudyba & Gregorio (2010)
	Diagnosis: neural network	Cognitive	Machine learning	Lopes et al. (2020)
	Predicting patient response to treatment	Prescriptive	Artificial intelligence	Wesdorp et al. (2021)
Resource allocation	Improving hospital management processes	Diagnostic	Artificial intelligence	Raghupathi & Raghupathi (2014)
	Identifying sources of resource demand to improve hospital efficiency	Descriptive	Artificial intelligence	Kudyba & Gregorio (2010)
	Healthcare utilisation risk score determination to manage claims costs	Predictive	Artificial intelligence	David et al. (2019)
Financial management	Data mining	Descriptive	Machine learning	Kudyba & Gregorio (2010)
	Network algorithms to identify health fraud risk	Predictive	Machine learning	Branting et al. (2016)
Disease modelling	Markov process to model disease progression	Descriptive	Artificial intelligence	Reddy et al. (2011)
	Mathematical modelling to conduct outbreak analytics	Predictive	Artificial intelligence	Barry et al. (2018)
	Markov process to model Covid-19 progression	Descriptive	Artificial intelligence	Giardano et al. (2020)
Health economics	Health technology assessments	Descriptive	Artificial intelligence	Choi et al. (2016)
	Cost-benefit, cost-effectiveness, cost-minimisation, cost-of-illness, and cost-utility analyses	Descriptive	Artificial intelligence	Rawlins et al. (2010)

5.2 This literature review has aimed to identify the gaps between analytics techniques and applications in the healthcare industry. A total of 23 use cases have been analysed of which 21 provided sufficient data to classify the use case using the application and technique frameworks introduced in sections 2 and 3 respectively. From this, the following is identified:

5.2.1 Most applications relate to the most rudimentary categories on the analytics maturity continuum (40% descriptive and 20% diagnostic). A minority of use cases considered more sophisticated applications on the analytics maturity continuum (5% prescriptive and 5% cognitive). This highlights the potential to improve the adoption of more sophisticated analytics applications in healthcare industry.

5.2.2 Most use cases utilised artificial intelligence techniques (60%) with the remainder utilising machine learning (40%). No use cases utilised deep learning techniques. This highlights the potential to utilise more sophisticated techniques in the healthcare industry.

5.2.3 Artificial intelligence techniques were utilised by 75% of descriptive applications; machine learning techniques were utilised by 25% of descriptive applications. Artificial intelligence techniques were utilised by 25% of diagnostic applications; machine learning techniques were utilised by 75% of diagnostic applications. Artificial intelligence techniques were utilised by 50% of predictive applications; machine learning techniques were utilised by 50% of predictive applications. Both prescriptive and cognitive applications only utilised artificial intelligence techniques. No direct relationship appears to exist between the sophistication of application and the sophistication of the technique utilised; the proportion of more sophisticated techniques utilised does not increase as the sophistication of the application increases on the analytics maturity continuum.

5.2.4 Most disciplines included in the literature review had three or more observable use cases whereas financial management and health economics had only two. This potentially highlights two areas where there is greater opportunity for analytics adoption. This paper is part of a larger body of research which is exploring this further.

6. DISCUSSION

6.1 The principles of the Actuarial Society of South Africa (ASSA) code of professional conduct require actuaries to undertake to deliver, throughout their careers, specialist and up-to-date actuarial expertise that is ethical and subject to professional oversight (Lowther & McMillan 2014). Accordingly, the Code requires members to undertake to deliver a quality service (ibid.). As asserted by Barton & Court (2012), advanced analytics is likely to become a decisive competitive asset in many industries and a core element in companies' efforts to improve performance. Actuaries should therefore remain abreast of the various analytics applications and tools, technologies and algorithms available to inform decision-making and problem solving. This would include keeping up to date on legal considerations associated with the use of AI and dealing with confidential and sensitive information. There is likely to be a reasonable amount of intersectionality with the work of academics in the medical ethics and legal fields.

6.2 Terblanche (2009) discusses demand for actuarial resources in the context of changes in the financial environment, the ability of other professions to solve problems and the expansion of the role of actuaries into wider fields. As organisations increase their use of analytics to inform decision-making (Król & Zdonek, 2020), actuaries need to ensure they are able to compete in an ever-changing world where the lines between professions such as engineering and data science are more blurred. The benefit of working in multi-disciplinary teams is also becoming increasingly apparent as actuarial professional discipline and judgement can be combined with various technical inputs to analytics design.

6.3 A clear distinction exists between analytics applications and techniques. Analytics applications relate to the nature of the business question being asked whereas analytics techniques relate to the methodology used to answer the question. Analytics applications therefore consider what happened (descriptive), why did it happen (diagnostic), what may happen in future (predictive), what actions should be taken in future (prescriptive), and what actions should be taken in future taking into account real-time monitoring (cognitive). Analytics techniques consider the specific programming technique utilised (artificial intelligence, machine learning or deep learning).

6.4 Analytics maturity models can be utilised to place an organisation's analytics maturity on the analytics maturity continuum. This is in effect a mechanism to measure or rank the extent to which analytics is being used to inform decision-making within an organisation (or industry). The purpose of measuring the extent to which analytics is applied in decision-making is to identify gaps and assist with putting in place a strategy to improve organisation-wide analytics adoption.

6.5 Understanding the difference between various analytics techniques is necessary to ensure that the optimal technique is utilised when considering the actuarial principles of materiality and proportionality. More complex algorithms require longer processing time and higher computing power which are associated with additional costs. An organisation should avoid heavy capital expenditure on technology to support more sophisticated analytics techniques if the same or similar results can be provided utilising less sophisticated methods. Similarly the benefit of investing in building analytic capacity needs to be optimised by ensuring that the full potential of applying techniques to risk management is realised. Sophistication should be introduced when there is a substantial improvement in accuracy of results.

6.6 A complex advanced analytics technique can therefore be used to address a business challenge that is solved by descriptive applications i.e. answering, "what happened". For example, a self-organising map (a type of artificial neural network) can be utilised to cluster consumer behaviour into homogenous groups in order to understand historical behavioural choices. The complexity of the technique utilised is not directly correlated with the purpose (application) for which it is utilised. A deep understanding of the problem being addressed as well as the technique being utilised is necessary in order to solve problems in a manner that align with materiality and proportionality actuarial principles. Therefore, from the analysis in this paper it is concluded that, while it is important to understand the placement on the analytics maturity curve and the level of sophistication of techniques applied, gap identification must consider the appropriateness of using more sophisticated techniques to address healthcare-related challenges.

6.7 Figure 3 illustrates the relationship between analytics applications on the analytics maturity curve and analytics techniques.

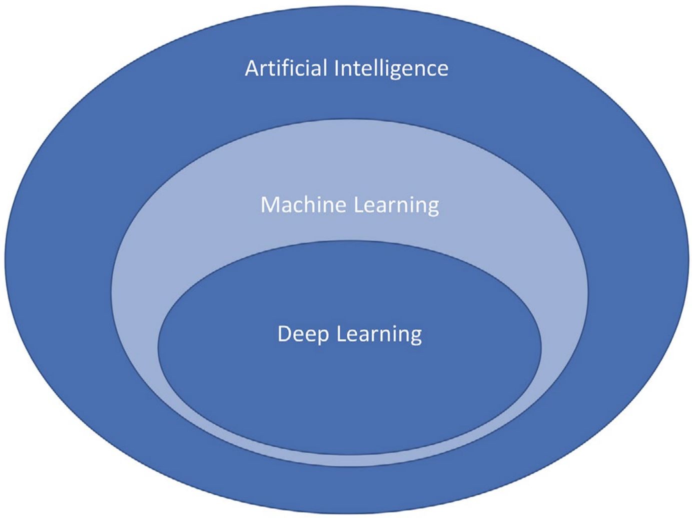

FIGURE 3. Linking analytics maturity curve (application) with analytics technique

6.8 Based on the literature review, the authors discuss analytics applications (the 'what') and analytics techniques (the 'how') separately. Research thus far has not considered an integrated view which highlights when it is most appropriate to utilise the techniques. The literature review has been conducted through desktop research using the following keywords: 'advanced analytics'; 'analytics maturity models'; 'analytics techniques'; 'machine learning'; 'artificial intelligence'; 'deep learning'.

6.9 In the context of healthcare applications, no direct relationship appears to exist between the sophistication of the application and the sophistication of the technique utilised since the proportion of more sophisticated techniques utilised does not appear to increase as the sophistication of the application increases on the analytics maturity continuum.

6.10 Most healthcare examples included in the literature review had three or more observable use cases whereas financial management and economics had only two. This potentially highlights two disciplines where analytics adoption lags compared to other disciplines. This paper is part of a larger body of work which explores this hypothesis.

7. CONCLUSION

7.1 The use of analytics in healthcare is becoming more prevalent due to the volumes of data involved as well as increasing accessibility of processing power to support more advanced techniques. It is apparent that there is an opportunity for these techniques to be applied to more advanced applications to realise the full potential in terms of risk management and enhancing health outcomes.

7.2 It is important for actuaries to remain abreast with the latest industry trends commonly used to inform decision-making. Analytics and, more specifically, advanced analytics has fast become an important strategic decision-making tool for organisations in various industries, and in healthcare in particular. Actuaries need to ensure they can understand and apply the various techniques available to solve business problems optimally and to apply appropriate judgement in the interpretation of results.

7.3 A deep understanding of the problem statement being addressed as well as the analytics techniques being utilised is necessary in order to solve problems in a manner that aligns with materiality and proportionality actuarial principles. A clear distinction has been established between analytics applications and analytics techniques.

7.4 Further, no direct relationship appears to exist between the sophistication of the application and the sophistication of the technique utilised. There is therefore potential for more sophisticated applications in the healthcare industry—the techniques utilised should be considered in context of actuarial materiality and proportionality principles.

7.5 This paper forms part of a larger body of research. Through this research, the following foundational principles have been established:
- There is a difference between analytics applications and techniques;
- Outcomes can be optimised by identifying in which cases particular techniques are applicable; and
- Researchers and healthcare practitioners can benefit from the appropriate use of analytics techniques.

7.6 The research that has been done in this area to date has a strong qualitative focus in regard to analytics maturity frameworks and a review of analytics techniques utilised in practice. Empirical evidence highlighting when best to apply the techniques in real world application remains an area for future research.

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