Proceedings of the 2018 Winter Simulation Conference
M. Rabe, A.A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, eds.

RH-RT: A DATA ANALYTICS FRAMEWORK FOR REDUCING WAIT TIME AT EMERGENCY DEPARTMENTS AND CENTRES FOR URGENT CARE

Navonil Mustafee
John H. Powell
Alison Harper

Centre for Simulation, Analytics and Modelling (CSAM)
The Business School
University of Exeter
Streatham Court, Rennes Drive
Exeter EX4 4ST, UK

ABSTRACT

Right Hospital – Right Time (RH-RT) is the conceptualization of the use of descriptive, predictive and prescriptive analytics with real-time data from Accident & Emergency (A&E)/Emergency Departments (ED) and centers for urgent care; its objective is to derive maximum value from wait time data by using data analytics techniques, and making them available to both patients and healthcare organizations. The paper presents an architecture for the implementation of RH-RT that is specific to the authors' current work on a digital platform (*NHSquicker*) that makes available live waiting time from multiple centers of urgent care (e.g., A&E/ED, Minor Injury Units) in Devon and Cornwall. The focus of the paper is on the development of a Hybrid Systems Model (HSM) comprising of healthcare business intelligence, forecasting techniques and computer simulation. The contribution of the work is the conceptual RH-RT framework and its implementation architecture that relies on near real-time data from NHSquicker.

1 INTRODUCTION

The UK National Health Service (the NHS) is going through a period of transition. Demand for NHS services is increasing while the component Trusts are being asked to make drastic cost savings and to manage their budgets even more robustly. Accident and Emergency (A&E) attendances in 2016 in England were 5.2% higher than in 2015 (roughly translating to an average of 2200 attendances/day in major emergency departments or EDs) and this contributed to an increasing number of patients breaching the 4-hour target (16.2% in 2016, compared to only 4.8% in 2011) (HCL 2017). To ease pressure and to meet the 95% standard in A&E (i.e., a minimum of 95% patients attending an A&E department should be either admitted, transferred or discharged within 4-hours of their arrival), the UK Government announced an extra £100 million A&E capital funding in its 2017 budget, with part of this funding being used for primary care streaming and co-locating GP (General Practitioner – primary care) practices within A&E departments (Gov.uk 2017). The support for clinical streaming in the A&E department, including streaming to co-located primary care services, was initiated by NHS England and NHS Improvement and was published in July 2017 (NHS Improvement 2017). Although GP co-location (including out-of-hours primary care) is not a new concept (Wilson 2005; Iacobucci 2014), its current emphasis is upon reducing the burden of primary care patients attending ED departments. However, there is little evidence to support such co-location strategies. A recent review by Ramlakhan et al. (2016) analyzed existing literature on GP-delivered, hospital-based unscheduled care services; it noted an increase in attendance (which the authors attribute to provider-induced demand), limited evidence of improved throughput and marginal cost savings per patient.

Our current work, although similar in objectives to the GP co-location strategy, is based on the vision articulated by The Keogh Review of urgent and emergency care (Urgent and Emergency Care Review Team 2013). This states that people with urgent but non-life threatening needs should be treated outside of hospitals by services that deliver care in or as close to people's homes as possible (e.g., Minor Injury Units (MIUs), Urgent Care Centers (UCCs)) while those with more serious or life threatening emergency needs are treated in centers having the very best expertise and facilities specific to those needs. Increased localization of the treatment of those with less serious needs will relieve pressure on the hospital-based emergency services, thus freeing up resources to cater for patients with more serious and life-threatening conditions such as severe chest pain, serious blood loss, choking and unconsciousness. The success of this partitioning policy is dependent on two related factors, namely the presentation of patients at the appropriate treatment facility and the capacity of the EDs, in particular, to cope with demand. Inevitably the capacity of EDs is finite, and it is highly desirable that patient demand be spread among the available facilities in a given region, so as to reduce waiting time and to shape demand, thus spreading the pressures on staff and facilities.

In response to these policies and requirements, we have worked with several NHS Trusts in the South West of England to investigate how existing data, already being captured at the urgent care centers, could be used to:

- Encourage patients to choose the appropriate type of treatment facility for their condition, so that only those with more serious needs present at the A&E. The aim of this is to reduce the overall demand on the A&E facilities by redirecting less serious cases to the more appropriate facilities of MIUs and UCCs, thus reducing waiting times at the A&E facilities.
- Shape demand at A&E facilities by encouraging patients needing such facilities to choose a destination with a lower waiting time.

We aim, thus, to influence destination choices made by prospective patients so as to aid NHS frontline staff in their day-to-day operations, firstly by improving the appropriateness of center choice and secondly by smoothing demand over inevitably stretched facilities, particularly those offering emergency treatment. We explain the effect (a) has on (b). Patients do not have a direct role in managing the operations of an urgent care facility. However, the decisions they take have a bearing on its performance. For example, when confronted with the need for urgent treatment, the intended users have to make location decisions as to the place of treatment. If they are unaware of the availability of urgent care services appropriate to meet their needs close to where they are located, they will usually choose to go to A&E as they are confident they will be seen and have their needs met (Mustafee et al. 2017a). This may lead to the overcrowding of A&E, while at the same time, MIU/UCCs that are located nearby may be operating under capacity; both cases will have operational implications.

Right Hospital-Right Time (RH-RT) is our high-level conceptual view of how wait-time data could be churned using descriptive, predictive and prescriptive analytics. Our aim is to derive maximum value from the resultant information and knowledge, and putting it to use for the benefit of both patients and the NHS. In our study, the NHSquicker platform (https://nhsquicker.co.uk/; H and CIN 2017a; H and CIN 2017b) provides data for the implementation of RH-RT. As the paper is being offered to a simulation conference, the focus of this work is on the prescriptive component of the RH-RT architecture, which could be realized using a Hybrid Systems Model, or HSM for short. The remainder of the paper is structured as follows. Section 2 provides an introduction on real-time data and Data Analytics (DA). In Section 3, we present our conceptual RH-RT framework which essentially shows how the different elements of DA can be used together for the analysis of wait time data. Section 4 provides an overview of NHSquicker. This leads on the implementation architecture for RH-RT which is based on data from NHSquicker (Section 5). We restrict the focus of our discussion to the prescriptive element of RH-RT through the use of Hybrid Systems Modelling (HSM). In the concluding section we outline some of the challenges of implementing NHSquicker/RH-RT and outline future work.

2 DATA ANALYTICS (DA)

DA solutions are data-driven. An understanding of data, its structure, the frequency of data update, etc. are important considerations which help to determine the suitability of specific DA approaches. Our discussion thus begins with an outline of what we mean by real-time operational data and its potential use in informing patients' A&E/MIU/UCC attendance choices (section 2.1). This is followed by a brief outline of the different forms of DA (sections 2.2, 2.3 and 2.4).

2.1 Real-Time Data in Urgent Care/A&E Context

Emergency Department Management Systems (EDMS) are widely deployed in healthcare facilities to collect, store and retrieve patient-specific information. The data captured by such systems also include non-clinical data, for example, date and time of arrival, mode of transport, the source of referral and postcode. The raw data can be effectively transformed into meaningful information with the objective of providing effective strategic, tactical and operational insights to decision-making (Evelson 2010). For example, EDMS like *Symphony* include features such as real-time monitoring of the 4-hour wait time data and real-time patient management (EMIS Health 2016). Data captured by such systems are subject to policies concerning regulation and governance of patient-specific data. This usually translates to data access being provided to mainly healthcare professionals, clinical audit teams and researchers with necessary approvals. However, considering that some of the data captured by EDMS are not of a clinical nature but are operations specific, making this data available to the wider group of stakeholders, including patients, can have a positive impact on the delivery of A&E services. Further, this may lead to a feeling of self-activation (taking control) and early reduction of anxiety among patients.

2.2 Descriptive Analytics

Descriptive analytics (DA), usually defined as Business Intelligence (BI) (Saxena and Srinivasan 2013; Chen et al. 2012), analyses and presents data using techniques such as descriptive statistics, data summaries and real-time reporting. It describes the ability of a business to collect, maintain, and organize knowledge, allowing decision-makers to quickly assess performance by visualizing aggregated data, often using Key Performance Indicators (KPIs) to compare current performance against targets for business objectives. While BI shares the same broad aim as DA more generally: to convert raw data into meaningful information, and information into insights for making better strategic, tactical and operational decisions (Evelson 2010; Haas et al. 2011) asserted that historical data alone, no matter how it is packaged and presented, remains simply a record of history which provides limited insights or solutions. It is arguable that the combined use of historical and real-time data can alleviate some of these criticisms. For example, NHSquicker (H&CIN 2017a; H&CIN 2017b) has been developed to make available real-time data, while also providing APIs that enable the download of historical snapshots with time stamps.

2.3 Predictive Analytics

The term predictive analytics is loosely defined in the literature. In its most general sense refers to any method which can support predictions about *what might happen* including data mining, forecasting, and mathematical approaches (Delen and Demirkan 2013; Shao et al. 2014; Waller and Fawcett 2013). More commonly, at the other end of the spectrum, predictive analytics is characterized far more specifically as data-driven machine learning methods for making predictions (Mortenson et al. 2015; Abbott 2014) and is often considered to be a subset of, or synonymous with, 'Big Data' applications (e.g., Koh and Tan 2005; Janke et al. 2016; Vidgen et al. 2017). Taking the broader perspective, forecasting describes a set of methods which have been used extensively in healthcare to predict events based on prior foreknowledge from historical data and other sources of information.

2.4 Prescriptive Analytics

Prescriptive tools inform decision making by suggesting a solution path, for example, simulation can anticipate the consequences of unforeseen interactions and prescribe interventions on the basis of tested scenarios (Marshall et al. 2015), while optimization is a prescriptive method as it suggests the 'best available' values for a given function (Hoad et al. 2015). Simulation models can be seen to be both predictive and prescriptive (Adra 2016), while optimization techniques are considered to be prescriptive methods (e.g., Shao et al. 2014).

3 RIGHT HOSPITAL-RIGHT TIME (RH-RT): CONCEPTUAL FRAMEWORK

This section presents our conceptual *Right Hospital-Right Time* (RH-RT) framework for the analysis of urgent care wait time data using methods from data analytics. The use of the framework is not reliant on a specific product/platform (e.g., *NHSquicker* or *WaitLess*) for its data needs, but rather based on four assumptions: **(a)** access to data which includes the current date and time, the waiting time, the number of patients waiting to be seen and the total number of patients in the department, **(b)** access to data feeds from multiple centers of urgent care (A&E, MIUs, UCCs, Walk-in Centers) located in a defined geographical area (e.g., NHS Trusts and Sustainability and Transformation Plan footprints(STPs)), **(c)** availability of near real-time data, and **(d)** availability of historical data. RH-RT comprises of the following six components – *data format*, *input*, *analysis*, *output*, *feedback* and *computation & storage.* As can be seen from Figure 1 below:

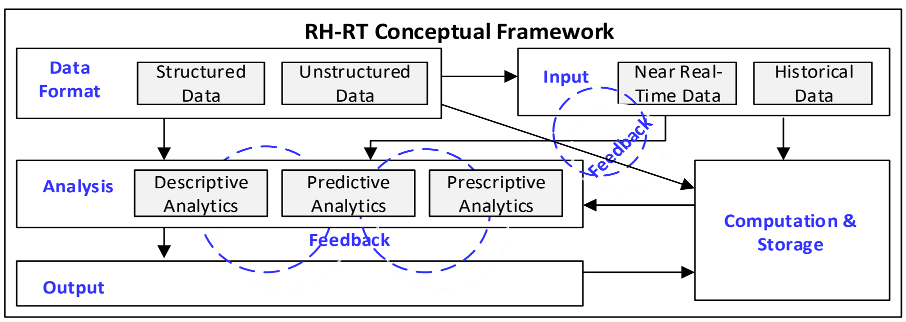

Figure 1: The Right Hospital – Right Time Framework illustrating the various high-level components, its constituent elements and feedback loops.

- The *Data Format* component comprises of two elements - *structured data* and *unstructured data*. Structured data could take the form of information exchange standards, database schema, etc. Unstructured data can take the form of emails, word documents, twitter and other social media feeds (e.g., patients may tweet waiting times they experienced in an A&E department, a hospital Trusts may report that an urgent care facility is unusually busy). Unstructured data may be used to supplement regular data updates and as historic data. However, we do not contemplate that unstructured data will replace the structural element of RH-RT.
- The *Input* component is made up of near real-time data and historical data. The data that is available for analysis is governed by the *Data Format* component (*Data Format* → *Input*).
- The *Analysis* component has descriptive, predictive and prescriptive elements. RH-RT does not impose specific algorithms, methods or techniques for the three aforementioned elements of the framework. For example, the healthcare analyst implementing the predictive element of RH-RT may use classical OR forecasting methods, statistical modelling, Machine Learning/Deep Learning or any other technique that can produce the output being expected by RH-RT. Similarly, the prescriptive element of RH-RT is not restricted to particular simulation or optimization techniques. The *Data Format* governs the algorithms and techniques that are used specifically in the Analysis

component (*Data Format* → *Analysis*). Both real-time data and historical data (the latter retrieved from storage systems) can be used by the algorithms performing the analysis (*Input* → *Analysis; Computation and Storage* → *Analysis*).

- The *Output* component represents the results of analysis performed by the RH-RT *Analysis* elements (*Analysis* → *Output*). The output may be stored as input for future analysis (Output → *Computational & Storage*)
- *Feedback* underlines the need for a joined-up approach when using the descriptive, predictive and prescriptive elements for data analysis and the potential of using the output from one form of analysis as the input to subsequent analysis (feedback is represented as dashed circles in Figure 1). Another important feedback loop is the one that intersects the input (near real-time data) and the analysis components of RH-RT. This loop highlights the need to constantly monitor the predictions with real-time data, to calibrate the analytical models.
- The *Computational & Storage* element signifies the importance of having the right infrastructure for data storage (required for the RH-RT input component - historical data) and computation (e.g., stand-alone storage and execution, Hadoop and MapReduce, Cloud Computing). RH-RT does not impose any particular model and it would depend on the volume and velocity of data (reference here to two fundamental characteristics of BigData) to identify the right storage and computation approach to enable real-time data processing (*Data Format* and *Input* → *Computation & Storage*).

4 NHSQUICKER

NHSquicker is a digital platform that makes available live waiting time data from A&E departments, Minor Injury Units (MIUs), Walk-in Centre (WICs) and Urgent Care Centers (UCCs) from multiple NHS Trusts in Devon and Cornwall. The platform comprises of an information exchange standard, a content management system, a mobile app (also called *NHSquicker*) and aspects of an evidence capture framework, in particular, app analytics. It has been developed by the *Health & Care IMPACT Network* (http://www.health-impact-network.info/), which is a collaboration between health and care organizations and universities, primarily in the South West of England. The purpose of the network is to improve delivery of health and care through applied research, knowledge dissemination and decision support. The network was founded through a collaboration between Torbay and South Devon NHS Foundation Trust (Directorate of Strategy & Improvement) and the University of Exeter Business School.

In the remainder of this section, we unpick the important elements of the platform, an understanding of which is essential to the ensuing discussion on the implementation architecture for RH-RT. We present a short overview of the data, the standard for information exchange (co-developed with our NHS partners), the backend content management system and the NHSquicker app. Note that the app is only one component of the overarching NHSquicker platform.

1. Data Feed and Frequency of Update: At the time of writing, data feeds are being received from 23 centers for urgent care (including five hospitals with A&E departments). We are working with the providers of a further six MIUs/UCCs/Walk-in centers to make their data live. The total of 29 centers belong to the following six NHS Trusts and one Medical Practice (Table 1) – *Torbay & South Devon NHS Foundation Trust (TSDFT)*, *Royal Devon & Exeter NHS Foundation Trust (RD&E), Northern Devon Healthcare NHS Trust (NDHT)*, *Royal Cornwall Hospitals NHS Trust (RCHT)*, *Plymouth Hospitals NHS Trust (PHT)*, *South Western Ambulance Service NHS Foundation Trust (SWASFT)* and *Claremont Medical Practice*. Currently, these data feeds are being received from ED information management systems like *PatientFirst* (RD&E), *Symphony* (TSDFT), *TracCare* (NDHT) and *Oceano* (RCHT). The frequency of data update is managed by individual trusts (usually 5-15 minutes).

2. Information Exchange Standard: We organized the *3rd Health & Care IMPACT event* in the University of Exeter Business School (June 2017) with the purpose of engaging with our partner NHS trusts to co-develop the design of the platform (H&CIN 2017c). One important objective of the event was to agree to one information exchange standard for sending data from the various ED management systems to our system. The data structure includes the Trust to which a center belongs (*trust_id*), information whether a center is an A&E department or a MIU (*department*), the longest waiting time (*waiting_time*), the number of patients waiting to be assigned to a clinician (*patients_waiting*), total number of patients in the department (*patients_total*), the opening and closing time of a center (*opening*, *closing*), its geographical coordinates (*long*, *lat*), etc. This data is sent to the NHSquicker backend using the JavaScript Object Notation (JSON) data-interchange format.

Table 1: Data Feeds for the NHSquicker Platform (as in Dec 2017).

Trust/ Practice	**Trust Name**	**Total**	**Type of Urgent Care Facility**	**Not Live**
RD&E	Royal Devon & Exeter NHS Foundation Trust	2	1 A&E + 1 MIU	
NDHT	Northern Devon Healthcare NHS Trusts	5	1 A&E + 3 MIU + 1 Walk-in Centre	1
SWASFT	South Western Ambulance Service NHS Foundation Trust	1	1 UCC	1
CMP	Claremont Medical Practice	1	1 UCC	1
RCHT	Royal Cornwall Hospitals NHS Trust	12	1 A&E + 10 MIU + 1 UCC	
T&SDFT	Torbay & South Devon NHS Foundation Trust	4	1 A&E + 3 MIU	
PHT	Plymouth Hospitals NHS Trust	4	1 A&E + 3 MIU	3
	TOTAL	**29 (including 6 sites that are not live)** *5 A&E, 20 MIU, 3 UCC and 1 Walk-in Centre*		

3. Content Management System (CMS): The platform is designed to work at the STP-level (rather than individual Trusts). Its underlying architecture is extensible; new centers can be added and their wait time data displayed, as long as they conform to the data standard. This is made possible using the backend CMS providing the functionality to create new API addresses (web services). The system creates one unique address for every center. Data from these centers are transmitted to their respective API addresses (web services).
4. NHSquicker App: The app provides 'digital nudges', or indirect suggestions, to inform patients of the urgent care services that are located in close proximity. The mechanism for delivering the 'nudge' is the ordered listing of services, in ascending order, based on waiting time plus travel time. Discussion on the specifics of the nudge algorithm is outside the scope of the paper and will be reported in a subsequent publication. The app also provides access to the Directory of Services (DOS) for Devon and Cornwall; this enables easy identification of alternative local health services like pharmacies, dentists and opticians. The app is available for Android and Apple devices. The app can also be accessed as a web-based application and supports Chrome, Firefox and Safari browsers (https://nhsquicker.co.uk).

5 RH-RT IMPLEMENTATION ARCHITECTURE FOR NHSQUICKER

In this section we present the implementation architecture for RH-RT and which is based on data from the NHSquicker platform – we collectively refer to this as **RH-RT/NHSquicker**. As the paper is for a simulation conference, we restrict the focus of our discussion to the prescriptive element of RH-RT through the use of HSM. The following two sub-sections provide an overview of HSM and map the RH-RT/NHSquicker HSM implementation to the different components of the overarching RH-RT framework.

5.1 Hybrid Systems Modelling (The Prescriptive Element of RH-RT/NHSquicker)

Hybrid Systems Modelling (HSM) can be defined as the combined application of simulation with methods and techniques from disciplines such as Applied Computing, Business Analytics, Computer Science, Data Science, Systems Engineering and OR. The objective of HSM is to build a better representation of the system by combining the wider array of discipline-specific approaches with computer simulation techniques (including hybrid simulation). In the context of HSM, these methods and techniques do not necessarily have to be combined with simulation in the *implementation / model development stage* of a M&S study*;* they could be applied to stages such as, *conceptual modelling*, *model verification and validation* (V&V) and *experimentation*. Application of HSM to one or more stages of a M&S study is referred to as a Hybrid M&S Study (Powell and Mustafee 2016; Mustafee et al. 2017b; Mustafee and Powell 2018).

The prescriptive element of our RH-RT is computer simulation. More specifically, the continuous stream of data made available through our platform could be used in the development of a **real-time A&E simulation**. Further, combining the descriptive and predictive DA approaches with simulation will enable the development of an **A&E Hybrid Systems Model.** Table 2 categorizes the individual methods and techniques based on DA terminology and the particular stages of a simulation study that these could be applied to. As our HSM proposes the use of forecasting methods and real-time data/BI (Healthcare Analytics) with DES (M&S), and we apply them to multiple stages of a M&S study, we contend that the model thus developed (A&E HSM) is an example of a Hybrid M&S Study (Powell and Mustafee 2016; Mustafee and Powell 2018).

Table 2: A&E HSM – The predictive element of RH-RT/NHSquicker.

DA Terminology	Methods/Techniques	Stage(s) of M&S Study
Descriptive Analytics	Healthcare Business Intelligence, i.e., real-time data from existing healthcare systems, its integration and summary statistics/KPIs	Input Data and Experimentation
Predictive Analytics	Forecasting methods based on historic data - refer to Harper, Mustafee and Feeney (2017) to see an example.	Input Data, Experimentation and Output Analysis
Prescriptive Analytics	Discrete-event Simulation	Model Implementation

5.2 Mapping of RH-RT/NHSquicker HSM Implementation to the RH-RT Framework

Table 3 refers to the RH-RT framework (Figure 1) and maps the use of the individual RH-RT components and elements (columns 1 and 2) in the implementation of RH-RT/NHSquicker (column 3). Although the focus of the paper is on prescriptive analytics (highlighted in bold in Table 3), descriptive and predictive elements have been included since we have argued for an HSM. Further, our approach is in line with the *Feedback*-centric viewpoint of RH-RT (Section 3), which is, "the need for a joined-up approach when using the descriptive, predictive and prescriptive elements for data analysis and the potential of using the output from one form of analysis as the input to subsequent analysis."

Table 3: Mapping RH-RT to the RH-RT/NHSquicker implementation.

RH-RT Components	**RH-RT Elements**	**RH-RT/NHSquicker Implementation**	**Further Information**
Data Format	Structured Data	Information Exchange Standard	Section 4.B
Input	Near Real-Time Data	Data feed from 23 centers of urgent care	Section 4.A
	Historic Data	Probability distributions from simulation study at Torbay Hospital	Section 6
Analysis **(Hybrid Systems Model)**	Descriptive Analytics	Healthcare Business Intelligence	Section 5.1
	Predictive Analytics	Forecasting Methods	Work-in progress
	Prescriptive Analytics	DES model of Torbay Hospital	See following text
Feedback		Mainly prescriptive analytics but also relying on Analysis-Output feedback	See following text
Output		Results of simulation (scenarios)	Work-in progress
Computation & Storage		Local file system storage; single computer execution	

At the time of writing, we have:

- Implemented a DES (Simul8™) model of the A&E department in Torbay Hospital (Torbay and South Devon NHS Foundation Trust).
- Completed the development of the NHSquicker app (now available to the public through Apple and Google app stores).
- Developed programs to download NHSquicker data at a certain frequency (30 minutes) and to extract the specific data items from the downloaded data. These will be used to populate variables and simulation elements in the Simul8™ model (queue length for entities/patients that have completed triage and are waiting to be allocated to a clinician in Major/Minor, waiting time, number of entities in the department).

We are currently experimenting with statistical and forecasting methods, such as regression modelling and autoregressive integrated moving average (ARIMA) models, to compute the predicted waiting time in three time-brackets (current time + 1 hour, +2 and +3 hours). The predicted time will aid real-time scenario analysis as it would serve as a benchmark, with pre-developed simulation scenarios being executed with the objective of decreasing the predicted time. We are working on the mechanisms to automate the A&E model execution process (i.e. as soon as new data is downloaded, it is parsed, the model variables are assigned relevant data items, and model execution starts). As our download and parser programs are written in Java, we are also considering the use of AnyLogic™ (which supports Java™ and is built on the Eclipse platform). Using AnyLogic™ would also offer us the possibility of geographical modelling using GIS. What we mean by this is, running scenarios where we have A&E models of multiple hospitals and are looking at transfer/reallocation of patients from one hospital to another (e.g., due to a major accident or terrorist incidence), and which would need to take into consideration the road network (available through AnyLogic's GIS implementation). As can be seen in Table 3, we are presently downloading data to a local computer. With time, and as more storage space is needed, this solution may no longer be feasible, and we will need to explore other options like cloud storage. However, the computation and storage element of RH-RT is receptive to change in the underlying technology.

6 CONCLUSION

Making real-time data available to patients can support *sensemaking*, that is, making sense of the complexities of the decision by constructing a mental model. A mental model is a form of knowledge that clarifies the interrelationships between key factors involved in a problem (Wieke 1985). This has been shown to improve comprehension of events and support predictions about outcomes (Bagdasarov et al. 2016). Ultimately the decision to attend a particular emergency care service lies with the patient, and factors such as perceptions of their clinical condition, wait-time tolerance, travel distance involved, past experiences and perceptions of available care available will all contribute to the final decision. The user plays an important role in the creation of the supply chain for urgent care treatment. The deployment of data analytics aims to support this system by making real-time analysis available to patients (this includes predicted future states and analysis of what-if scenarios), enabling patients to make an informed choice on treatment options and potentially changing ED attendance behavior.

The present focus of our work is on the development of a forecasting model to make wait time predictions that use historical data with real-time data on wait time and travel time. We are also working on the development of a real-time simulation model which uses data feed from NHSquicker and patient flow management systems.

ACKNOWLEDGMENTS

We acknowledge the funding received from the University of Exeter (Open Innovation Platform) and the Torbay Medical Research Funds towards the development of the *NHSquicker* platform. We would like to thank Andrew Fordyce, Susan Martin, Alaric Moore, Nic Harrison, Jessica Newton and our other NHS partners for their inputs and contribution to the study.

REFERENCES

Abbott, D. 2014. *Applied Predictive Analytics*. Hoboken, NJ: Wiley.

Adra, H. 2016. "Realtime Predictive and Prescriptive Analytics with Real-time Data and Simulation". In *Proceedings of the Winter Simulation Conference*, edited by T. M. K. Roeder et al., 3646-3651, Piscataway, New Jersey: IEEE.

Bagdasarov, Z., J. F. Johnson, A. E. MacDougall, M. S. Logan, S. Connelly, and M. D. Mumford. 2016. "Mental Models and Ethical Decision Making: The Mediating Role of Sensemaking". *Journal of Business Ethics* 138(1):133-144.

Chen, H., R. H. L. Chiang, and V. C. Storey. 2012. "Business Intelligence and Analytics: From Big Data to Big Impact". *MIS Quarterly* 36(4):1165-1188.

Delen, D. and H. Demirkan. 2013. Data, Information And Analytics As Services. *Decision Support Services* 55(1):359-363.

EMIS Health. 2016. Real-time Patient Information in Unscheduled Care Settings. https://www.emishealth.com/products/symphony, accessed 23.07.2018.

Evelson, B. 2010. *The Forrester Wave™: Enterprise Business Intelligence Platforms*. Forrester Research Inc. www.forrester.com/go?objectid=RES56280, accessed 23.07.2018.

Gov.uk. 2017. Accident and Emergency (A&E) Departments To Get More Funding (published 21.04.2017). https://www.gov.uk/government/news/ae-departments-to-get-more-funding, accessed 23.07.2018).

Haas, P. J., P. P. Maglio, P. G. Selinger, and W. Tan W. 2011. "Data is Dead..Without What-if Models". In *Proceedings of the Very Large Database (PVLDB) Endowment* 4(12):1486-1489.

Harper, A., N. Mustafee, M. Feeney. 2017. "A Hybrid Approach using Forecasting and Discrete-event Simulation for Endoscopy Services". In *Proceedings of the 2017 Winter Simulation Conference*, edited by W. K. V. Chan et al., 1583-1594, Piscataway, New Jersey: IEEE.

H&CIN. 2017a. NHSquicker: Informing ED/MIU Attendance Choices through 'Digital Nudges'. Health & Care IMPACT Network. http://www.health-impact-network.info/projects/edmiu-application/, accessed 23.07.2018.

H&CIN. 2017b. NHSquicker iOS app. https://itunes.apple.com/gb/app/nhsquicker/id1312817040?mt=8, accessed 23.07.2018.

H&CIN. 2016c. The 3rd Health & Care IMPACT Network Event (University of Exeter, 21st June 2017). http://www.health-impact-network.info/event-archive/3rd-impact-event/, accessed 23.07.2018.

Hoad, K., T. Monks, and F. O'Brien . 2015. "The Use of Search Experimentation in Discrete-event Simulation Practice". *Journal of Operational Research Society* 66(7):1155-1168.

House of Commons Library. 2017. "*Accident and Emergency Statistics: Demand, Performance and Pressure"*. Commons Briefing papers SN06964.

Iacobucci, G. 2014. "All Emergency Departments should include GP Staff, say Experts". *BMJ: British Medical Journal* online pp.349. https://doi.org/10.1136/bmj.g4654, accessed 23.07.2018.

Janke, A, D. Overbeek, K. Kocher, and P. Levy. 2016. "Exploring the Potential of Predictive Analytics and Big Data in Emergency Care". *Annals of Emergency Medicine* 67(2):227-236.

Koh, H. and Tan, G. 2005. "Data Mining Applications in Healthcare". *Journal of Healthcare Information Management* 19(2):64-72.

Marshall, D., L. Burgos-Liz, M. Ijzerman, W. Crown, W. Padula, P. Wong, K. Pasupathy, M. Higashi, and N. Osgood. 2015. "Selecting a Dynamic Simulation Modeling Method for Healthcare Delivery Research – Part 2: Report of the ISPOR Dynamic Simulation Modeling Emerging Good Practices Task Force". *Value in Health* 18(2):147-160.

Mortenson M. J., N. F. Doherty, and S. Robinson. 2015. "Operational Research from Taylorism to Terabytes: A Research Agenda for the Analytics Age". *European Journal of Operational Research* 241(3):583-595.

Mustafee, N., J. H. Powell, S. Martin, A. Fordyce, and A. Harper. 2017a. "Investigating the Use of Real-time Data in Nudging Patients' Emergency Department Attendance Behaviour". In *Proceedings of the 2017 Spring Simulation Multi-Conference*, April 23-26, Virginia Beach, VA. Article 6.

Mustafee, N., S. Brailsford, A. Djanatliev, T. Eldabi, M. Kunc, and A. Tolk. 2017b. "Purpose and Benefits of Hybrid Simulation: Contributing to the Convergence of its Definition". In *Proceedings of the 2017 Winter Simulation Conference*, edited by W. K. V. Chan et al., 1631-1645, Piscataway, New Jersey: IEEE.

Mustafee N. and J. H. Powell. 2018. "From Hybrid Simulation to Hybrid Modelling". In *Proceedings of the 2018 Winter Simulation Conference*, edited by M. Rabe et al. (accepted), Piscataway, New Jersey: IEEE.

NHS Improvement. 2017. "Clinical Streaming in the A&E Department" (published 7.7.2017). https://www.england.nhs.uk/publication/clinical-streaming-in-the-accident-and-emergency-department, accessed 23.07.2018.

Powell, J. H and N. Mustafee N. 2016. "Widening Requirements Capture with Soft Methods: An Investigation of Hybrid M&S Studies in Healthcare". *Journal of the Operational Research Society* 68(10):1211-1222.

Saxena, R. and A. Srinivasan. 2013. *Business Analytics: A Practitioners Guide*. NY: Springer-Verlag.

Shao, G., S. Shin, and S. Jain. 2014. "Data Analytics using Simulation for Smart Manufacturing". In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk et al., 2192-2203, Piscataway, New Jersey: IEEE.

Urgent and Emergency Care Review Team. 2013. "Transforming urgent and emergency care services in England Urgent and Emergency Care Review" – End of Phase one review.

http://www.nhs.uk/NHSEngland/keogh-review/Documents/UECR.Ph1Report.FV.pdf,accessed 23.07.2018.

Vidgen, R., S. Shaw, and D. B. Grant. 2017. "Management Challenges in Creating Value from Business Analytics". *European Journal of Operational* Research 261(2):626-639.

Waller, M. A. and S. E. Fawcett. 2013. "Data Science, Predictive Analytics, and Big Data: A Revolution that will Transform Supply Chain Design and Management". *Journal of Business Logistics* 34(2):77-84.

Wieke, K. E. 1995. *Sensemaking in Organizations*. Thousand Oaks, CA.

Wilson, H. 2005. "Co-locating Primary Care Facilities within Emergency Departments: Brilliant Innovation or Unwelcome Intervention into Clinical Care?". *The New Zealand Medical Journal* online 118:1221.

AUTHOR BIOGRAPHIES

NAVONIL MUSTAFEE is Associate Professor of Operations Management and Analytics and the Deputy Director for the Centre for Simulation, Analytics and Modelling (CSAM) at University of Exeter Business School. He is an interdisciplinary researcher and is interested in the use of quantitative methods and applied computing for decision making. His research interests are in simulation methodologies and hybrid simulation, data analytics, hybrid systems modelling and 'digital' behaviour change interventions. He is the founder and co-chair of the Health and Care IMPACT Network, a collaboration between University of Exeter Business School and health and care partners in South West of England and has led the development of NHSquicker. His e-mail address is n.mustafee@exeter.ac.uk and his webpage is http://sites.google.com/site/navonilmustafee/.

JOHN POWELL is Professor in Strategy at University of Exeter Business School. His research interests are in systems modelling of strategic situations, scenario planning and modelling, knowledge in strategy, knowledge management. He has a PhD in strategic conflict from Cranfield University, UK. His email address is j.h..powell@exeter.ac.uk.

ALISON HARPER is a Post Graduate Research (PGR) research student at University of Exeter Business School. Her research interests are in healthcare analytics and M&S. Her e-mail address is ah596@exeter.ac.uk.