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A comprehensive and integrated hospital decision support system for efficient and effective healthcare services delivery using discrete event simulation

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ABSTRACT

The difficulty that hospital management has been experiencing over the past decade in balancing demand and capacity needs is unprecedented in the United Kingdom. Due to a shortage of capacity, hospitals cannot treat all patients. We developed a whole hospital-level decision support system to assess and respond to the needs of local populations. We integrated a comparative forecasting approach and discrete event simulation modelling using Hospital Episode Statistics and local datasets. It is clear from the literature that this level of whole hospital simulation model has never been developed before (an innovative decision support system). First, the demands of all hospital specialties were forecasted, and the forecasts were embedded into the simulation model as input. Secondly, a simulation model was developed to capture the patient pathway of all specialties. The model integrates every component of a hospital to aid with efficient and effective use of scarce resources (e.g., staff and beds). As a result, the hospital can meet the increasing demand with its current resources. According to the scenario analysis, the hospital bed occupancy rate will reach the national target (i.e., 85%), and the total hospital revenue will increase by approximately 13%, with a 10% increase in A&E and outpatient and a 20% increase in inpatient demand. In conclusion, the hospital-level simulation model can become a crucial instrument for decision-makers to provide an efficient service for hospitals in England and other parts of the world.

1. Introduction

High hospitalization rates create significant pressure on hospital managements, influenced by various factors such as population growth, alcohol and tobacco consumption, and stress. The population is a crucial factor, characterized by both growth and aging. In the United Kingdom (UK), individuals aged 65 and above accounted for one-sixth of the population in 2010, and this number is projected to rise to approximately one-fourth by 2050 [1].

The aging population directly impacts hospital visits, with the 65+ age group constituting the highest proportion of Accident and Emergency (A&E) admissions [2]. UK A&E departments lack resources to meet increasing demand, failing to discharge 95% of patients within 4 h [3]. Arrivals to A&E have risen by 26% since 2006/07, but the departments have not met the target since 2014/15, worsening annually [4] and 2018a), compromising patient care. In addition, over the past decade, the number of attendances and admissions to outpatient and inpatient specialties have increased by around 27% and 32%, respectively [5]. Bed occupancy rate has exceeded the 85% target level in England [6]. The level of difficulties experienced by the hospital management over the past decade in terms of balancing demand and capacity needs is at an unprecedented level.

Due to financial constraints in the National Health Service (NHS), hospitals do not have the opportunity of recruiting additional doctors and nurses or increasing bed capacity. If nothing can be done in terms of capacity, then hospital management needs to find efficient and effective ways of utilizing existing resources.

A hospital is a complex system and modelling each and every service within A&E, inpatient and outpatient departments/specialties is a challenge. A typical hospital is made up of more than 25 specialties providing treatment across inpatient and outpatient services. The complexity of a hospital system is due to the interaction effect between

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services. Each specialty has several departments and wards with an array of human resources, made up of consultants, doctors, nurses, healthcare assistants, technicians, radiographers, and many more. For instance, a typical hospital in England has an average of 100,000 inpatient admissions, 350,000 outpatient attendances across approximately 30 specialties, along with 125,000 A&E admissions per annum [7] and 2018b).

It is clear from the figures that modelling at this level of detail is not just a challenge but extremely difficult. The literature around modelling healthcare services is vast and extremely rich. In the majority of instances (if not all) they concentrate around modelling a single disease, service, department or a specialty, and at best a few of these services combined [8]. However, at the hospital level this can be deemed to be inadequate. A director or a chief executive officer (CEO) of a hospital needs a model that assists them both at strategic and operational level. A whole hospital modelling framework is an absolute necessity due to the interdependencies between components of hospitals. For example, increasing demand does not just happen within a single specialty, it is a phenomenon across the hospital, thus a model examining the impact across all specialties is necessary, so that the management can intervene accordingly. At the time when this model was under development, another nearby hospital had closed down. This is a typical example where such a model can be extremely beneficial, because the knock-on effect was on all the services within the hospital under study. Therefore, a comprehensive modelling framework is needed that brings together all specialties and services at a hospital within a single decision support system (DSS).

A DSS is a user-friendly tool designed to produce solutions to real-life problems through computer aided information systems [9]. The DSS which is needed to be developed for this study should guide key decision makers to ensure their system is able to cope with current and future demand, and able to stress test the system not just focusing on a single specialty or a service, but its impact on the hospital as a whole. No department, service or specialty is an independent entity, they are all interconnected. For example, a consultant does not just work in an outpatient setting, but their expertise is utilized with inpatients too. Also, if there are bed shortages within a specific specialty, patients can be admitted to other specialties.

A number of modelling approaches (i.e., system dynamics, queueing theory and Markov chain modelling) are used to model patient flow in hospitals by Refs. [10–12]. Amongst many modelling methods and approaches, Discrete Event Simulation (DES) is chosen as it enables us to capture the whole hospital at a sufficient level of detail, with the flexibility of further developing a user-friendly interface to get hospital managers to engage with the model. Furthermore, unlike other methods, DES is able to simulate random behaviours of systems (i.e., length of stay, waiting time and number of follow ups) and is able to track an individual patient's path in a hospital. DES can also model events occurring at any discrete point in time and considers different features of patients, e.g., age, gender, disease [13]. We acknowledge that an alternative simulation technique, Agent Based Simulation (ABS), could be chosen for modelling. For our problem domain, DES is superior to ABS for balancing demand and capacity and modelling processes. When focusing on process modelling, DES is generally the preferred choice. ABS is suitable for modelling individual behavior, like disease spread. Note that in ABS, a modeler builds state charts for each agent type and for the environment. The behavior emerges with interaction between agents, such as patients and human resources. More detail on the choice for simulation modelling methodology in healthcare exists in Ref. [14].

A whole hospital model can answer many key questions at specialty and/or departmental level. For example, what will be the required number of beds? How many consultation hours will be needed for outpatient and inpatient services? What percentage of future demand will be met with the available resources (i.e., doctors, nurses, beds)? Will specialties require additional resources, if yes, which ones and how many? What will be the financial implications of change? What will be the expected and future levels of operating theatres and outpatient clinics, and their utilizations? Many more questions of this type could be added.

The core objectives of the DSS are as follows.

1) Establish and develop a patient pathway of an entire hospital, with the aim of assisting key decision makers at a hospital in England. The goal is to eliminate the deficiencies of the current and past studies around modelling hospitals within a single framework.
2) Create a novel method that merges DES with healthcare demand forecasting. Currently, no comprehensive research exists on forecasting attendance/admission demand for all specialties and integrating it into a hospital simulation model.
3) Develop a user friendly DSS to examine key performance metrics of a typical NHS Trust for future planning. Decision makers will then be able to balance demand and capacity, thus providing an opportunity to intervene well in advance.

The remaining sections of the paper are organized as follows: Section 2 reviews simulation modelling in healthcare. Section 3 covers data analysis for forecasting and simulation modelling, including processes, parameters, and experimental design. Section 4 discusses study results, metrics, and what-if scenarios. Section 5 concludes the study.

2. Literature review

2.1. Simulation modelling in healthcare settings

Healthcare spending constitutes a substantial portion of national budgets in many countries, and citizens strive for cost-effective solutions. Professionals involved in healthcare system design prioritize addressing citizens' concerns and finding ways to enhance service delivery while minimizing costs. Operations Research (OR) techniques and methodologies play a crucial role in addressing these objectives. The academic literature on this subject is extensive and offers valuable insights. For example [15], edited a special issue for evaluating OR in healthcare and presented a wide range of papers from optimization of hospital operations to assessment of public health policies. They conclude that OR and Industrial Engineering (IE) techniques can aid better management of healthcare [16]. presents a European perspective and emphasize the need for analysis at operational and strategic levels, for better delivery of healthcare. Special focus reviews also exist, such as planning in healthcare by Ref. [17] and Emergency Departments (ED) by Ref. [18].

One way of achieving better healthcare is to study patient flows in terms of healthcare delivery pathway and health outcomes [19]. reviewed the patient flow modelling literature for acute community services from these two perspectives. The motivation behind their reviews is to evaluate strategic change of governments to shift acute services from hospitals to community, closer to patients' home. Their review highlights the complexity in patient pathway modelling and sheds light on various methodologies presented in the literature. They conclude that, besides time dependent analytical methods, simulation models are needed to evaluate the effects of alternative patient pathways. An earlier review by Ref. [20]; emphasized the importance of modelling patient flows and presents techniques and methods for better decision making.

When it comes to modelling patient flows, various comprehensive modelling methodologies are utilized, including Business Process Modelling Notation (BPMN) and Unified Modelling Language (UML) [21]. presents a new methodology based on UML Activity Diagram (UML AD) to model patient flows. Their modelling methodology is suitable for enhanced reasoning and appropriate for better representation. Likewise, Proudlove et al. [78] suggests that BPMN has the potential to engage stakeholders in healthcare modelling projects.

Use of novel simulation methodologies, such as Agent Based

Modelling (ABS) have been used in the healthcare context [22]. [23]; for example, developed an ABS model to analyze patient and healthcare professionals' behaviors in ED. Especially in agent state tracing and efficient execution of simulation models, ABS is an appropriate method for analyzing patient flows. On the other hand, hybrid simulation approaches, are found to be beneficial for patient flows [24]. discusses the usefulness of Discrete Event Simulation (DES) and ABS or a combination of both techniques and System Dynamics (SD) in healthcare context. Using multi method simulation techniques has greater potential to depict patient flows.

The current healthcare systems are facing challenges in coping with the growing population, rising hospitalization rates, and constraints on resources and budget. Therefore, demand-capacity modelling of healthcare systems has gained significant popularity. Hybrid approaches are employed to address challenges within healthcare systems. Consequently, the collaboration of diverse disciplines can simplify the resolution of complex problems. Simulation modelling is a versatile approach that integrates various disciplines and is commonly employed in hybrid studies. For example [25], integrated forecasting techniques and simulation to manage demand and capacity of hospital emergencies, whereas [26] developed a hybrid model to provide a strategic planning for bed capacity in a hospital. In addition [27], combined simulation with particle swarm optimization model to improve cancer diagnosis pathways. Between 2019 and 2022, the COVID-19 pandemic has been the primary focus of research. Extensive studies have been conducted in the field of health, covering various aspects related to COVID-19.

Table 1
Comparison of the studies developing the entire hospital simulation models.

Criteria	Studies					
	[35]	[36]	[37]	[38]	[39]	Current Study
Journal	Health Care Management Science	Journal of the Operational Research Society	ACM Transactions on Modelling and Computer Simulation	International Journal of Medicine Informatics	Health Systems	N/A
Type of simulation	DES	SD	DES	DES	DES	DES
Data	- Collected data	- National HES Dataset - Collected data	- National HES Dataset	- Collected data	- National HES Dataset - Local data	- National HES Dataset - Local data - Literature
Hospital main services (i. e., A&E, inpatient and outpatient)	- Inpatient	-A&E -Inpatient -Outpatient	-A&E -Inpatient (ward level) -Outpatient	-Inpatient	-A&E -Inpatient -Outpatient	-A&E -Inpatient -Outpatient
Transfers between services and departments (i.e. A&E to inpatient)	No	-A&E to Inpatient (IP) -Outpatient (OP) to IP	-A&E to IP (Non-elective inpatient admissions are referred from both General Practitioner (GPs) and A&E only) -OP to IP (Inpatient elective referrals are made from only outpatient departments in the model)	No	-A&E to IP (all non-elective admissions are assumed to arrive from A&E)	-A&E to every department within IP -A&E to every department in OP -OP to every IP
All individual departments	Applied to only one specialty. However, it can be used for every specialty	No	Yes	Yes	A&E and only 10 main specialties	All individual departments (1 A&E, 25 OP, 26 IP)
Single processes or complex modelling	Complex Modelling	Single Process	Complex Modelling	Single Process	Single Process	Complex Modelling
Theatre	Yes	No	No	No	Yes	Yes
Outpatient clinic slots	No	No	Yes	No	Yes	Yes
Wards	Yes	Yes	Yes	Yes	Yes	Yes
Waiting List	No	No	Yes	No	Yes	Yes
Type of distributions	Theoretical	N/A	Theoretical	Theoretical	Theoretical	OFD
Follow Ups	No	No	Yes (Percentages are used)	No	Yes (Average number of follow ups)	Yes (Observed frequency distribution (OFD) for each OP)
Rebook (Did not attend and Cancellation)	No	No	No	No	No	Yes
Financial Inputs and Outputs	No	No	No	No	Average Healthcare research group (HRG) tariff	OFD based on diagnostics from HRG tariff for A&E, and for every specialty in IP and OP
Outputs	-Specialty Level	- Hospital level (Bed occupancy rate)	- Hospital level (4 outputs)	- Specialty Level (3 outputs)	-Hospital level (Required bed capacity (RBC), Total session utilization (TSU)) -Specialty level	-Hospital level (Demand coverage ratio (DCR), Bed occupancy rate (BOR), Total revenue (TR)) -Specialty level (6 outputs for A&E, 10 outputs for each OP, 12 outputs for each IP)
Outputs per department	No	No	No	Yes	Yes	Yes
Multidisciplinary Study (Integrability)	No	No	No	Yes (with simply optimization)	Yes (with simply forecasting)	Yes (with comparative forecasting and optimization)

A&E: Accident and emergency department, BOR: Bed occupancy rate, DCR: Demand coverage ratio, DES: Discrete event simulation, DNA: Did not attend, GP: General Practitioner, HES: Hospital Episode Statistics, HRG: Healthcare research group, IP: Inpatient specialties, OFD: Observed frequency distribution, OP: Outpatient specialties, RBC: Required bed capacity, SD: System dynamics, TR: Total revenue, TSU: Total session utilization.

Noteworthy studies include research by Ref. [28] on modelling hospital occupancy and by Ref. [29] on measuring hospital preparedness. These studies contribute to the broader scientific efforts against COVID-19. In addition, analytical approaches have been used to model patient flow, for example, queuing theory by Refs. [30–32]; and Markov chain modelling by Ref. [33].

Our review reveals that modelling for patient flows in hospitals is needed for two reasons; First, evaluating options for improvement behind hospitals' walls, and second, tackling the complexity developed by the interrelationship between hospital departments. The first reason is related to patient demand management, in other words "gate keeping" such as primary care and ancillary services outside of hospitals. The second reason, however, is about the hospital care processes, their dependencies, and the existence of feedbacks. This study aims at filling the gap in the literature by modelling hospitals holistically to aid decision making at strategic level.

2.2. Entire hospital simulation modelling

The literature around modelling healthcare services is vast and extremely rich. In the majority of instances (if not all) they concentrate around modelling a single disease, service, department or a specialty, and at best a few of these services combined [8]. It is difficult to develop a whole simulation model imitating all the processes within a hospital setting [34]. In the literature, there are very few studies that have developed simulation models for an entire hospital where all the relevant data are collected and analyzed for each specialty within an inpatient and outpatient setting. These studies have been reviewed in greater detail in Table 1 and the deficiencies in the literature related to entire hospital simulation modelling are presented. Column 7 in Table 1 (current study) clearly differentiates our study compared to the hospital simulation models developed in the past. In this respect, our study has filled a major gap in the literature by eliminating these deficiencies. For example [35], developed a generic framework to model level of resources (i.e., beds, staff, and operating theatre) by capturing variability, uncertainty, limited resources and complexity of a hospital. This study focused on modelling only inpatient beds and theatre processes and therefore other components of the hospital are not included, for example, A&E department, outpatient services and referrals between and within services. Utilized system dynamics technique to model a complete hospital system, including two hospitals. However, this technique is not ideal for queueing networks with resources, as emphasized in their research. Instead of individually modelling each main specialty, they employed a submodel to represent all main specialties. Furthermore, bed occupancy rates for each inpatient specialty were not measured; instead, bed occupancy was calculated at the hospital level [37]. developed a comprehensive hospital model comprising A&E, inpatient, outpatient departments, and waiting list simulations. Their model represents a district general hospital and captures interactions among key hospital components. The authors assert that the model facilitates strategic decision-making and, to some extent, operational-level choices. Furthermore, their model relies on limited analysis of Hospital Episode Statistics (HES) and Patient Administration System (PAS) data. Our model, in this current study, differentiates from Ref. [37] model in two ways; first our model is more complex and therefore can be used for operational level decisions, and second, the data analysis part of our model is more elaborated than their model and therefore can generate additional insight that is required for better customization [38]. developed a whole hospital simulation model using DES technique for the purpose of allocating beds in a hospital. However, they focused solely on inpatient specialties, and ignored A&E department, outpatient specialties and interactions amongst these services. Non-elective patient admissions are considered in a stochastic nature taking into account arrival time with theoretical distributions. On the other hand, elective patient admissions are planned and are known in advance. In addition, length of stay for each ward is modelled with theoretical distributions instead of using frequency observed distributions. Theatre processes and utilization along with financial inputs and the required consultant and nurse hours were not considered [39]. developed a decision support tool to better understand future key performance metrics of a hospital. Limitations of this study include the following: 1) instead of the entire hospital, 10 main specialties along with A&E department was selected, hence not an entire hospital simulation model as claimed by the authors, 2) transfers between specialties were not considered, and 3) distribution for length of stay and other key input parameters was not established.

There are several healthcare simulation case studies provided by Simul8 [80]. It is an excellent resource with a wide range of applications for readers to better understand the use of the Simul8 software in practice. Each model tackles a single disease, pathway or a specific problem in hand (e.g., bed capacity/management, operating rooms). However, further details about the individual models in the form of a publication or a report are not available, thus it's impossible to determine the inner workings of the model, such as the care setting, input parameters (data collection and analysis), verification and the validation process.

Furthermore, none of the models developed by Simul8 tackles an entire hospital's services as presented in this study, including all specialties within inpatient, outpatient, and A&E. Our model does not just deal with a specific element of a hospital (e.g., bed management) but it considers an array of issues at specialty level, including theatres, outpatient clinic slots, bed management, staff management, patient readmissions, laboratory, tariff per diagnostic and so on. More importantly we provide all the relevant details for hospitals to be able to replicate this within their own setting.

2.3. Hospital demand forecasting

In the literature, hospital demand has been widely forecasted by comparing many forecasting methods [40]. conducted an exhaustive literature review and determined that most studies are aimed at forecasting A&E departments. For example, A&E demand was predicted using forecasting methods by Refs. [41,42]; [43–50,76], and [51]. On the other hand [52,53], forecasted hospitalizations for the pediatric patients with asthma. In addition [54], was interested in forecasting hospital bed demands [55]. focused on estimating bed occupancy rate in an A&E department, whereas [56] predicted length of stay of an A&E department [57]. estimated daily number of patients in surgery [58]. developed linear regression models to forecast the demand for radiology services. The autoregressive integrated moving average (ARIMA), exponential smoothing (ES) and multiple linear regression were found to be the most widely used techniques [59]. In light of the global COVID-19 pandemic that occurred between 2019 and 2022, a significant proportion of healthcare studies have been centred around COVID-19. Likewise, forecasting studies within this research domain have predominantly concentrated on this particular pandemic, such as the daily COVID-19 cases by Ref. [60]; intensive care unit bed demand by Ref. [61]; hospital bed capacity by Ref. [62]; case, death and hospital occupancy rate by Ref. [63]. On the other hand, a number of forecasting studies have focused on specific diseases, for example, mental health prediction by Syed Mohamed et al. [81], heart disease by Refs. [64,65]; and stroke prediction by Ref. [66].

3. Data and methods

In this study, a decision support system (DSS) is developed by combining comparative forecasting techniques and discrete event simulation for demand and capacity planning in the hospital. For this, the predicted demand is obtained from forecasting techniques instead of using presumptive demand to embed as input in the simulation model. A step-by-step guide is presented as a flow diagram illustrating how the two techniques are combined in Fig. 1. All required hospital data are extracted from the HES dataset over the period of the study. The

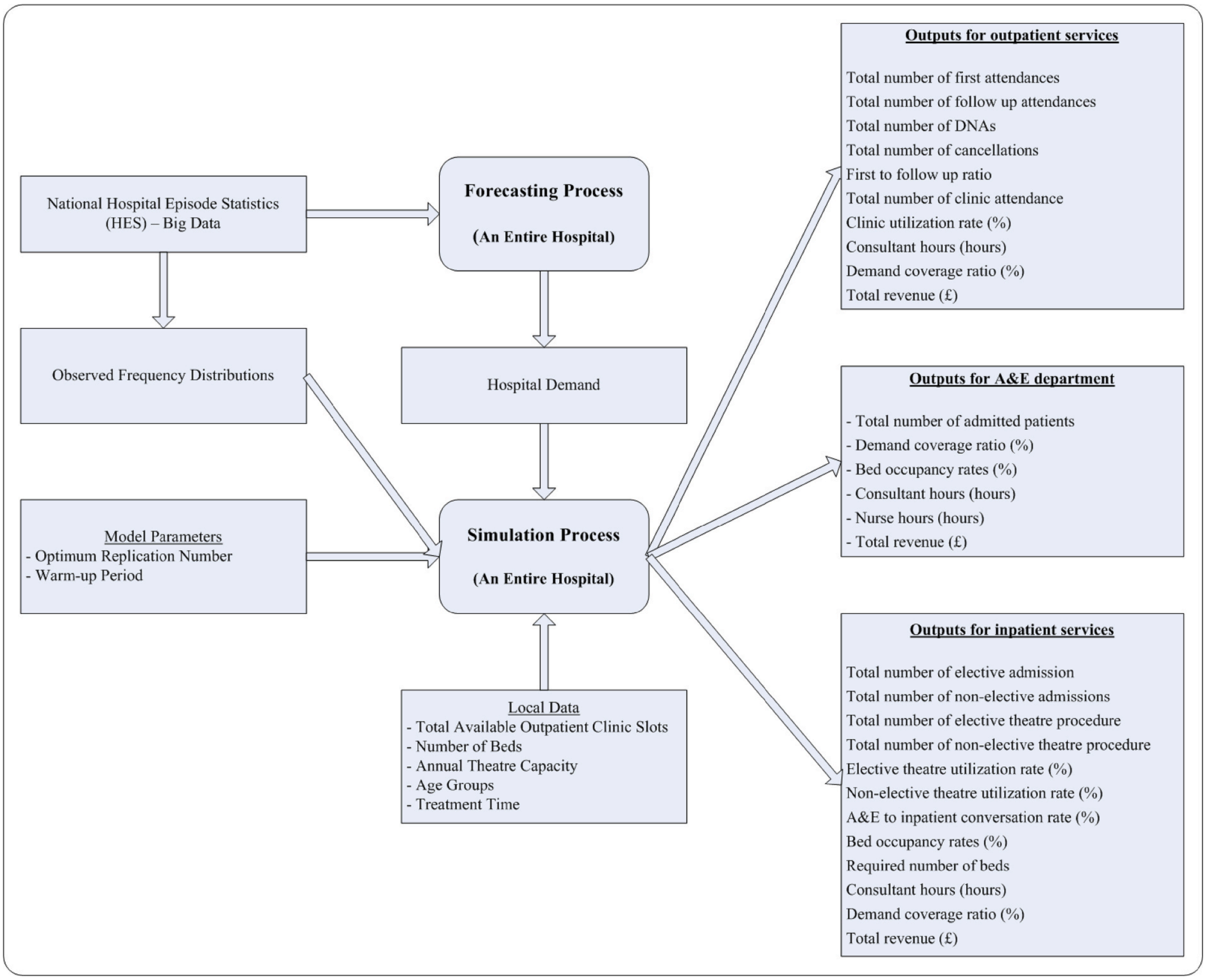

Fig. 1. The structure of the decision support system combining whole hospital simulation model with comparative forecasting methods.

required data is used in both demand forecasting and parameter estimation of the statistical distributions for the simulation model. These inputs along with model parameters, financial inputs and local data provided by the hospital are embedded into the whole hospital simulation model. The model then generates current and future levels of key output metrics for each specialty as seen in Fig. 1. Theoretical concept of discrete event simulation is explained in Section 3.2.2.

3.1. Data sources

The Department of Health in the UK releases its national database annually, the Hospital Episode Statistics (HES). The HES data set contains personal, medical, and administrative details of all patients admitted to, and treated in, NHS hospitals in England. There are more than 80 million records for each financial year. A financial year is from 1 April to 31 March the following year. The HES data set captures all the consultant episodes of patients during their stay in hospital. During a hospital stay, a patient might encounter several successive episodes, collectively known as a spell.

The data were provided in a txt format and necessary steps were taken to import the data into Microsoft SQL Server version 12.0, so that database programming could be carried out to prepare the data for analysis. Initial checks were made to ensure that the data sets provided contained encrypted NHS numbers for matching purposes. The data period is from 01/04/10 to 31/03/13 (three financial years).

The total number of observations in the A&E dataset over the data period in England is 65 m records, 15 m inpatient admissions, and 175 m outpatient attendances as seen in Table 2. We extracted all inpatient, outpatient and A&E data sets corresponding to the hospital of interest, i.e., 248,910 A&E arrivals with 86 variables, 996,134 outpatient attendances with 130 variables and 191,462 inpatient admissions with 414 variables.

The inpatient and outpatient datasets were further partitioned into 30 distinct specialties (e.g., cardiology, ophthalmology, trauma and orthopedics) to ensure all specialties within the hospital are considered as part of our forecasting and simulation modelling. For each specialty, activity related data (daily, weekly, and monthly inpatient admissions and outpatient attendances) along with hundreds of other variables (see Table 3) were extracted and analyzed, and distributions were established as part of input parameters into our simulation model.

Where required data is not available in HES, local data was provided by the hospital for inpatients and outpatients for each specialty, including, number of inpatient beds; number of doctors and nurses;

Table 2
Number of patient activities in England per financial year.

Specialty	2010/11	2011/12	2012/13	Total
A&E department	21,380,985	21,605,067	21,802,377	64,788,429
Outpatient	57,728,023	58,204,060	59,382,240	175,314,323
Inpatient	4,954,622	5,071,890	5,140,044	15,166,556
Total	84,063,630	84,881,017	86,324,661	255,269,308

Where Number of A&E arrivals, number of outpatient activities (i.e., first and follow up attendances and DNAs) and number of inpatient admissions. DNA: Did not attend.

Table 3
Activity related data in trauma and orthopedics outpatient and inpatient specialty over the data period.

Trauma & orthopedics outpatient specialty					
	Age groups	Attendance	DNA	Cancellation	Total
First attendances	Age group 1 (0–15)	6070	472	1401	7943
	Age group 2 (16–35)	5435	864	1161	7460
	Age group 3 (36–50)	5910	602	1590	8102
	Age group 4 (51–65)	6567	339	1730	8636
	Age group 5 (65+)	7385	326	1965	9676
Follow up attendances	Age group 1 (0–15)	7174	1132	2169	10,475
	Age group 2 (16–35)	8126	1855	2120	12,101
	Age group 3 (36–50)	12,019	1741	3419	17,179
	Age group 4 (51–65)	15,823	1336	4602	21,761
	Age group 5 (65+)	20,263	1439	6313	28,015
Trauma & orthopedics inpatient specialty					
Age groups	Elective	Non-elective	Total	Age groups	Elective
Age group 1 (0–15)	310	640	950	Age group 1 (0–15)	310
Age group 2 (16–35)	1231	805	2036	Age group 2 (16–35)	1231
Age group 3 (36–50)	2210	824	3034	Age group 3 (36–50)	2210
Age group 4 (51–65)	3121	826	3947	Age group 4 (51–65)	3121
Age group 5 (65+)	3655	2144	5799	Age group 5 (65+)	3655

Where DNA is Did not attend.

inpatient annual theatre capacity; percentage of patients having a surgery; outpatient clinic slots; A&E shifts, number of A&E triage rooms, and A&E clinic room availability (a comprehensive list of input parameters extracted from HES and local data are illustrated in Appendix A to C for a single specialty).

3.2. Methods

3.2.1. Demand forecasting

Hospital demand is predicted by using quantitative forecasting methods since patient admissions, outpatient attendances and A&E admissions are used as an input into the simulation model. The data was divided into two: the training set (financial years 2010/11–2011/12) and the validation set (financial year 2012/13).

In the literature, hospital demand has been widely forecasted by comparing many forecasting methods. The autoregressive integrated moving average (ARIMA), exponential smoothing (ES) and multiple linear regression were found to be the most widely used techniques [50]. [67] affirm that the seasonal and trend decomposition using loess (STL) method effectively separates time series datasets into seasons and trends. Consequently, the STL function (STLF) method can be a reliable forecasting technique. Hence, we compared this method with three others.

A prediction period for one specialty (e.g., an inpatient setting) might generate accurate forecasts but can be ineffective for other specialties or services. A hospital level forecasting modelling framework for the management to adapt and use in hospitals has been developed by Ref. [59]. Therefore, we have compared different forecasting periods to determine the optimal periods (i.e., daily, weekly, and monthly) to determine demand for outpatient, inpatient and A&E services.

The stepwise linear regression involves the use of dummy variables, e.g., the daily estimation includes variables for days of week, months of year, and variables related to UK public holidays (a holiday, a day before a holiday and a day after a holiday). The STLF method converts data to seasonal data using STL (The Seasonal and Trend Decomposition using Loess) decomposition. A non-seasonal forecasting technique is used to estimate values, which are then re-seasonalized using the previous year's seasonal component. (Hyndman et al., 2016). In this study, the following packages in R is applied in order to select the best ARIMA, ES, the STLF methods and stepwise linear regression, respectively: the auto.arima(), the ets(), the stlf() functions [68], and the stepAIC() functions [79].

We consider three forecasting periods (daily, weekly, and monthly) for each outpatient and inpatient specialty at the hospital. The A&E department is forecasted daily due to the high patient volume. Specialties with less than 1% of the total patient activity are grouped as "other specialty," ensuring that all specialties are accounted for. "Other specialty" for outpatient services consists of orthodontics, plastic surgery, medical oncology, geriatric medicine, radiology, chemical pathology, and allied health professional episode. "Other specialty" for inpatient elective is composed of plastic surgery, anesthetics, dermatology, neurology, rheumatology, geriatric medicine, and obstetrics whereas it for inpatient non-elective involves ear, nose and throat (ENT), ophthalmology, oral surgery, accident and emergency, anesthetics, gastroenterology, endocrinology, clinical haematology, medical oncology, neurology, rheumatology, general medical practice, clinical oncology, radiology and allied health professional episode.

In total 760 forecasting models were developed, made up of the following.

- 19 outpatient specialties x 2 (first and follow up referrals separately) x 3 periods (daily, weekly, and monthly) x 4 forecasting methods, which is 456 models for outpatients.
- 16 inpatient specialties (for elective admissions) x 3 periods (daily, weekly, and monthly) x 4 forecasting methods, which is 192 models for inpatients.
- 9 inpatient specialties (for non-elective admissions) x 3 periods (daily, weekly, and monthly) x 4 forecasting methods, which is 108 models for inpatients.
- A&E is forecasted daily only, thus 1 × 4 forecasting methods.

The selection criterion is the mean absolute scaled error (MASE), where the numerator is the mean absolute error of the forecasting method, and the denominator is the mean absolute error of the naïve method [69]. We have chosen to use the mean absolute scaled error (MASE) method because it can be used in comparison of forecasting studies carried out for different time horizons [69]. Using MASE, 64 best forecasting models are selected out of 760 models, i.e., 38 forecasted demands for outpatient specialties, 25 for inpatient specialties, and 1 for A&E. Table 4 illustrates the entire process for Trauma and Orthopedics specialty and the remaining specialties are shown in Appendix D and E.

The best forecasting result for the A&E department is daily stepwise linear regression with the lowest MASE value 0.90. The best forecasting method and period for trauma & orthopedics specialty are highlighted in grey in Table 4.

3.2.2. Simulation modelling

3.2.2.1. Conceptualizing hospital patient pathway. The first stage of the pathway mapping was to research the current practices within the

Table 4
Forecast accuracy values for the trauma & orthopedics specialty.

Specialty	Forecasting Models	Daily			Weekly			Monthly		
		Parameters	TS	VS	Parameters	TS	VS	Parameters	TS	VS
Outpatient (First referral)	SLR	SLR	0.47	**0.65**	SLR	0.93	1.04	SLR	0.75	1.32
	ARIMA	(3,1,3)	0.79	0.87	(4,0,0)	0.78	0.91	(1,0,1)	1.00	0.86
	ES	(A,A_d,N)	0.85	0.87	(A,A_d,N)	0.80	1.11	(M,A,N)	1.14	4.66
	STLF	STL+(A,N,N)	0.89	1.10	STL+(A,N,N)	0.77	1.54	STL+(M,N,N)	1.15	1.65
Outpatient (Follow-up referral)	SLR	SLR	0.45	0.93	SLR	0.80	1.63	SLR	1.23	2.12
	ARIMA	(2,1,2)	0.78	0.92	(3,1,1)	0.80	0.91	(0,1,0)	0.96	0.96
	ES	(A,A_d,N)	0.83	0.85	(M,N,N)	0.82	0.89	(M,N,N)	0.93	0.98
	STLF	STL+(A,N,N)	0.95	**0.53**	STL+(M,N,N)	0.80	1.35	STL+(M,N,N)	0.46	1.26
Inpatient (Elective)	SLR	SLR	0.46	0.89	SLR	1.28	1.63	SLR	1.09	2.50
	ARIMA	(2,1,3)	0.74	**0.87**	(0,1,1)	0.92	1.21	(1,0,0)	0.95	1.20
	ES	(A,A_d,N)	0.89	0.88	(A,N,N)	0.93	1.21	(A,N,N)	0.96	1.11
	STLF	STL+(A,N,N)	0.84	1.00	STL+(A,N,N)	0.42	1.32	STL+(A,N,N)	0.55	1.84
Inpatient (Non-elective)	SLR	SLR	0.81	0.81	SLR	1.00	0.89	SLR	1.06	1.91
	ARIMA	(0,1,1)	0.75	0.74	(0,1,1)	0.86	**0.67**	(1,0,0)	0.96	2.83
	ES	(A,N,N)	0.75	0.74	(A,A_d,N)	0.86	0.68	(A,N,N)	0.96	1.12
	STLF	STL+(A,N,N)	0.80	1.02	STL+(A,N,N)	0.67	1.08	STL+(A,N,N)	0.72	2.56

Where ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise Linear Regression, STLF: The function of the seasonal and trend decomposition -method, TS: Training Set, VS: Validation Set.

hospital. This included utilizing publications from the literature, which allowed us to draft a baseline patient pathway within a hospital setting, including a high-level mapping of A&E, inpatient and outpatient pathway. Once the initial pathway is established, the second phase consisted of structured interviews with hospital consultants, nurses, clinical and financial directors.

The interviews were conducted face to face sharing the initial diagrammatic representation of the pathway. Each stage of the pathway was discussed with the panel taking account of their opinions and adjusting the pathway in 'real-time' as comments were made. The objective of this process is to explore the entire hospital pathway in the eyes of the experts and identify the important areas of development. It is also crucial to establish a pathway that is generic enough so that it is applicable to all NHS providers in England.

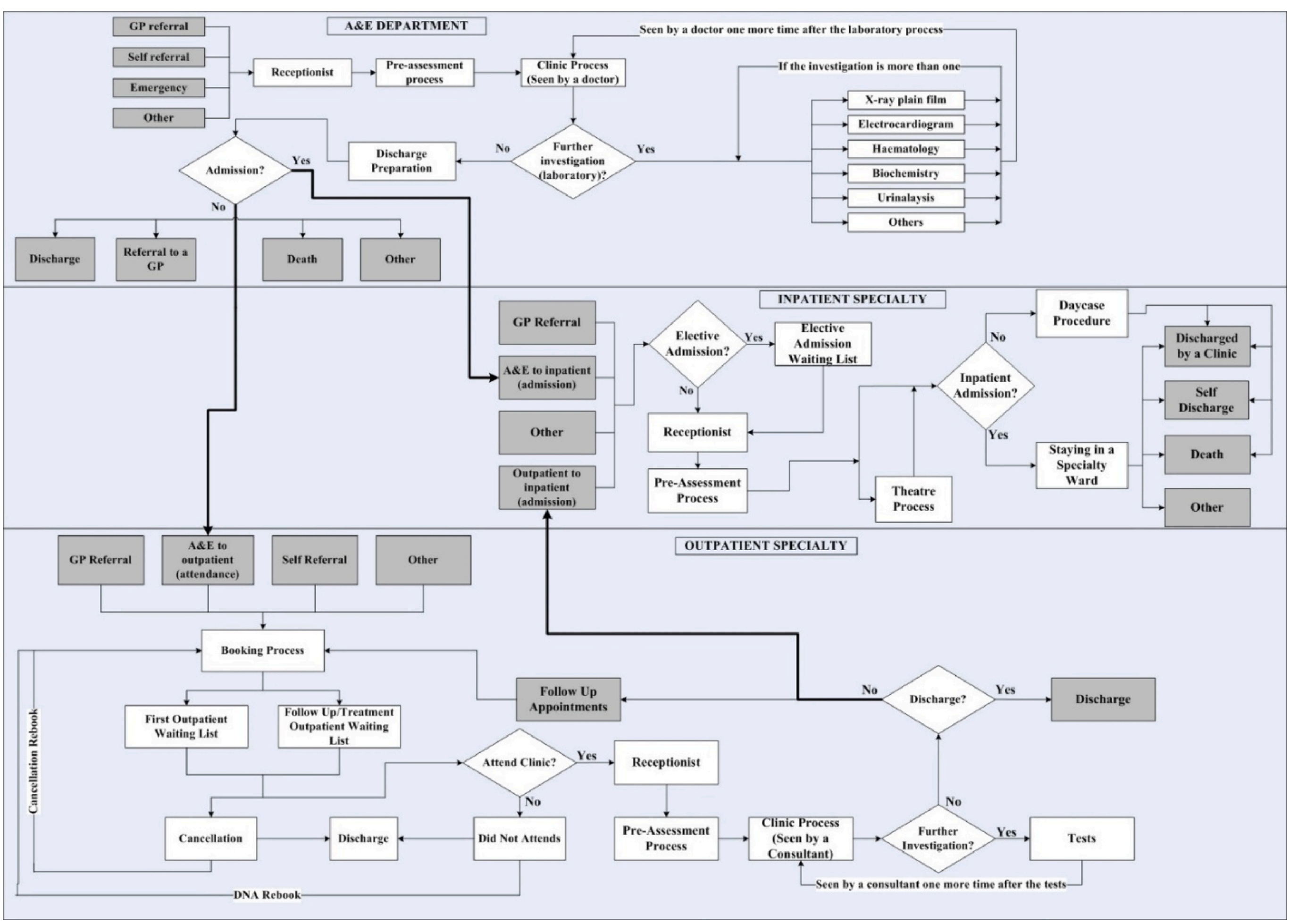

Fig. 2. High-level conceptualization of the hospital.

According to the interviews the typical care system in place in England, within inpatient, outpatient, and A&E services, comprises a complex set of services offered in and out of hospital. In this context, the pathway consists of three parts: A&E department, outpatient, and inpatient specialties in Fig. 2. Also, the interactions among the departments were also considered.

In this pathway, there are four different patient arrival types in the A&E department: patients can be referred from GPs, self-admission, emergency, or others (i.e., referral from educational establishments and general dental practitioner). Upon arriving to A&E, patients are registered by the receptionist and pre-assessment process (e.g., blood pressure) is carried out by a nurse. Patients then wait to be seen by a doctor. Doctors may request further investigations, such as X-ray, urinalysis, biochemistry, etc. Depending on patient's condition, they can either be admitted to inpatient care, discharged back to primary care; discharged to an outpatient department, discharged by death, or discharged home with no further action.

Patients can be referred to outpatient specialties either from GPs, self-attendance, from A&E department of the same hospital, and others (i.e., referral from optometrist and general dental practitioner). Patients may be booked for outpatient attendance after referral. At this point, some patients may cancel their appointments in advance or not attend the clinic without prior notice (some of these patients may rebook an appointment for a later date). Once a patient comes into an outpatient specialty, they check in at the reception and wait for treatment. If needed, a diagnostic procedure can be carried out before assessment and in some cases a treatment procedure could also be carried out by a consultant. After consultation, patients can either be discharged home, or can be admitted to an inpatient department if further treatment is necessary or referred to the outpatient specialty for follow up treatments.

Patients in a typical inpatient specialty are referred in the following ways: patients can be referred from GPs, from an A&E department or outpatient specialty of the same hospital and others (i.e., dental casualty department). Admission is also divided by two types: elective and non-elective. Elective admission consists of an appointment made prior to admission, whereas non-elective admission comprises patients who are mostly referred from A&E department and in some cases GPs. Elective patient waits to be admitted to inpatient specialty, anything from a few days to 18 weeks. After patient arrival and booking process, pre-assessment is performed, and it is decided whether patient is admitted to a specialty ward for care or not. If patient is not admitted to a ward, a day case procedure is carried out. Otherwise, patient is admitted, and a theatre process is carried out if needed. Then, the patient can either be discharged home or discharged due to death.

3.2.2.2. Input parameters. As the decision support system aims to model the entire hospital, there are a significant number of input parameters. Inputs to the model are related to patient demand as determined using forecasting techniques, treatment (pathways, percentage of patients falling into each specialty, discharges, length of stay), staffing (staffing levels, staff availability), and cost (staff salary, costing of each service). A full list of parameters is given in Appendix A to C for a single specialty. The vast majority of the input parameters are pre-determined through exhaustive analysis of HES and local hospital data. On a small number of occasions, experts were consulted during meetings. Note that all the input parameters are prepopulated and can be customized by the service provider if the users deem this to be necessary to fit their geographical area.

Input parameters for all the specialties were obtained as well as the trauma & orthopedics outpatient and inpatient specialty as presented in Appendix A to C. A&E, inpatient and outpatient demands were prepared as daily inputs into the simulation model. The referrals from A&E to inpatient specialties (for non-elective admissions) and to outpatient specialties were estimated accordingly.

Distributions play a crucial role in simulation modelling. We utilized various distributions to capture different aspects of the simulation, such as preparation time, treatment time, and time to discharge for the A&E department. Similarly, we considered distributions for variables like first appointment time, number of follow-ups, and intervals between follow-up treatments for outpatient specialties. Additionally, we incorporated distributions for first admission time and length of stay for inpatient specialties. All distributions were estimated for each age group separately (i.e., 0–15, 16–35, 36–50, 51–65, 65+), resulting in 600 distributions as follows.

- 19 outpatient specialties for first attendances x 2 observed frequency distributions (i.e., time for first appointment and number of follow-ups) x 5 age groups, 190 distributions in total for outpatients
- 19 outpatient specialties for follow up attendances x 2 observed frequency distributions (i.e., number of follow-ups and length between follow-up treatments) x 5 age groups, 190 distributions in total for outpatients (for follow up attendances),
- 16 inpatient specialties for elective admissions x 2 observed frequency distributions (i.e., time for first admission and length of stay for elective) x 5 age groups, 160 distributions for inpatients (for electives).
- 9 inpatient specialties for non-elective admissions x 1 observed frequency distribution (i.e., length of stay) x 5 age groups, 45 distributions for inpatients (for non-electives).
- 1 A&E department x 3 observed frequency distributions (i.e., time to treatment, treatment time, time to discharge) x 5 age groups, 15 distributions in total.

Observed frequency distributions were established using the Freedman-Diaconis Rule [70] to specify the optimum width of observed frequency distributions.

We estimated the distributions for the frequency of patient attendance in outpatient clinics for follow-up treatments throughout the year.

Furthermore, the duration of follow-up treatment for outpatient clinic patients was determined by analyzing the time between consecutive treatments for the same health condition. The time interval between each patient's follow-up appointments within each specialty was used to establish the distribution of the follow-up treatment duration. On the other hand, the length of stay in an inpatient specialty is calculated as the duration between a patient's admission to the ward and their discharge.

Financial inputs were taken from published reports by the Department of Health [77] and Department of Health and Social Care (2013). The average cost of an A&E admission in 2013/14 financial year was £124 per person. Healthcare Research Groups (HRGs) is an indicator which classifies similar clinical "conditions" or "treatments" in terms of level of resources used in healthcare systems [71]. An HRG Code was linked to each patient when calculating total revenue for outpatient (first and follow up attendances) and inpatient specialties (elective and non-elective admissions).

Inputs related to resources (i.e., bed, triage room, staff), outpatient clinic slots and inpatient annual theatre capacity were provided in collaboration with the hospital. For example, 36,700 outpatient clinic slots were available for the trauma & orthopedics outpatient specialty. In addition, total number of annual theatre capacity for elective and non-elective admissions were 8024 and 3011 procedures, respectively.

3.2.2.3. Developing simulation model. Developing a comprehensive simulation model to replicate all aspects of an entire hospital is challenging [34]. In the literature, there are very few studies that have developed simulation models for an entire hospital where all the relevant data are collected and analyzed for each specialty within an inpatient and outpatient setting. As defined in the conceptual model, and visualized in Fig. 3, we developed a DES model using Simul8 simulation

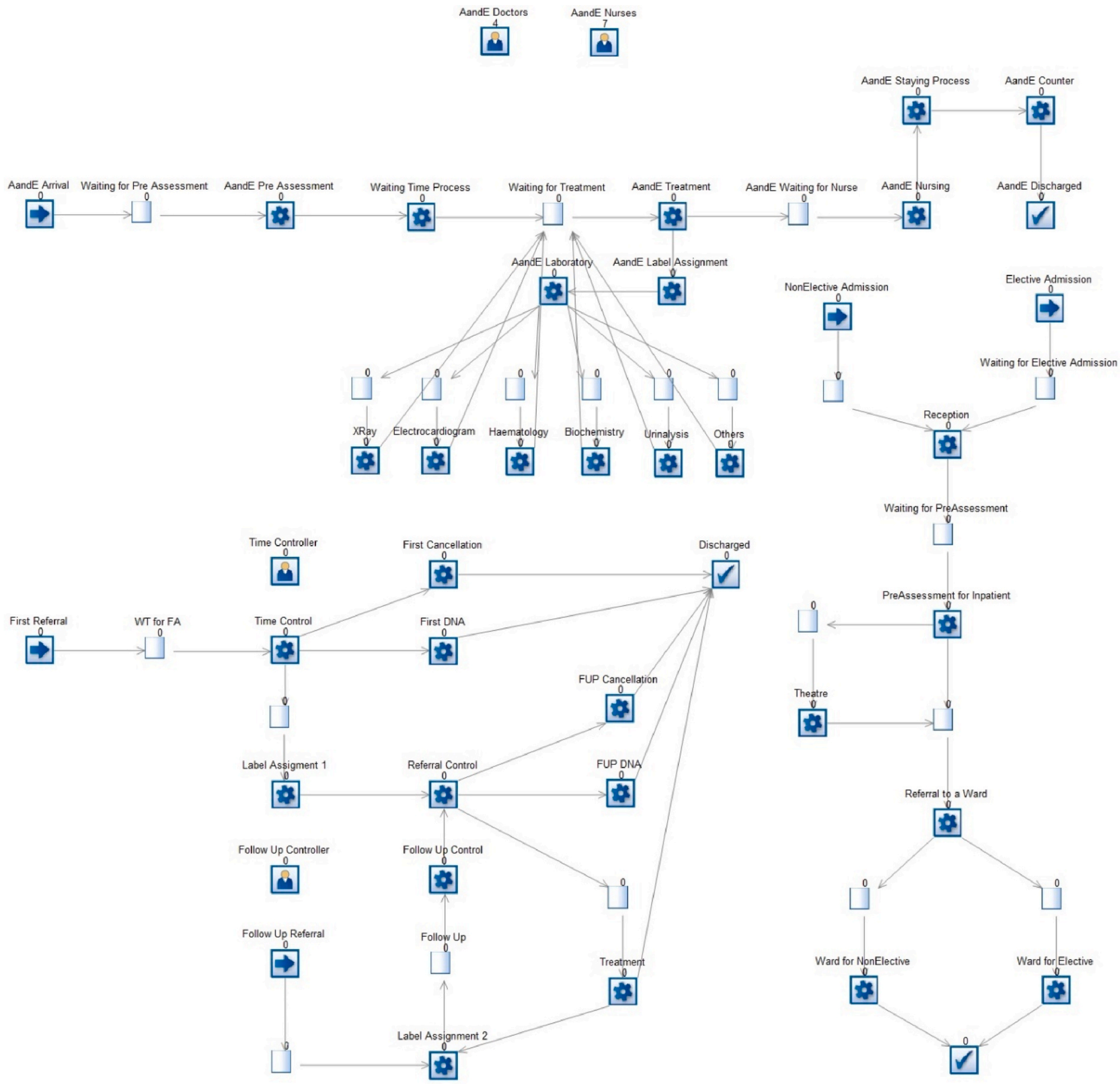

Fig. 3. High-level simulation model of the hospital.

software. A high-level representation is depicted in Fig. 3. The simulation model consists of all departments (i.e., A&E, outpatient, and inpatient specialties) and all specialties (i.e., general surgery, urology, and orthopedics), along with the interactions between A&E, outpatient, and inpatient specialties. Moreover, the feedback mechanism, (appointment rebooking typically faced in outpatient specialties) and system inefficiencies (cancellations and did not attend) are embedded into the simulation model.

The "AandE Arrival" entry point is made up of four arrival modes (i.e., GP referral, self-referral, emergency, and other) as shown in Fig. 2. Patients at the A&E department arrive based on estimated monthly theoretical interarrival time distributions. They are categorized into age groups based on statistical distributions. Following their arrival, patients undergo pre-assessment, typically performed by a nurse. Patients are then asked to further wait to be seen by an A&E doctor. In the 'AandE Clinic Process', if a doctor requests a further investigation, patients are referred to the laboratory area, such as X-Ray and electrocardiogram. An investigation bundle is assigned to each patient according to the distribution obtained from data. For example, if a patient has first investigation (X-Ray) and a second investigation (Electrocardiogram), the patient visits X-Ray area first followed by an electrocardiogram test. Patients are then further assessed by the A&E doctor and relevant treatment is decided. Following that, patients undergo preparation for discharge through the "AandE Discharge Preparation" process. A decision is then made among five discharge modes, as depicted in Fig. 2. These modes include admission to inpatient care, discharge back to primary care, discharge to an outpatient department, discharge due to death, or discharge to home with no further action. In this model, there are four distinct types in relation to process times: 1) pre-assessment time (triage), 2) treatment time (by clinician), 3) discharge time (post treatment), 4) total time in A&E, i.e., from arrival to discharge. Relevant distributions have been established for (1), (2) and (3), and (4) is an output.

A portion of A&E department patients are referred to the hospital's outpatient clinics, illustrating the interconnectedness within hospitals where one department's output becomes another department's input. Complex synchronization rules are implemented, such as scheduling an outpatient clinic appointment for A&E patients when needed. Patients wait for their appointment date based on observed frequency distributions related to age groups and specialty type. Patients have the option to cancel their appointments in advance through the "First Cancellation" work center or may not show up at the clinic, handled by the "First DNA" work center. First-time and follow-up patients are directed to the waiting area, "FUP Cancellation" or "FUP DNA" work centers, using the "Referral Control" work center. At this stage, some follow-up patients may cancel their appointments in advance through the "FUP Cancellation" work center or fail to attend the clinic through the "FUP DNA" work center. However, all first-time patients and some follow-up patients who wish to attend the clinic are guided to the waiting area for pre-assessment. A consultant at the outpatient clinic carries out diagnostic and/or treatment procedures through the "Outpatient Clinic Process" work center. The decision for follow-up appointments is made by the consultant after the treatment. If the patient does not require a follow up treatment, a discharge procedure is carried out. Otherwise, each patient, who needs a follow up appointment, is assigned a number of follow up according to observed frequency distributions estimated by taking into account age groups and type of specialty. Patients then wait at home for their follow up appointment. The assigned number of follow up decreases by one as they attend the clinic. Patient repeats this cyclical process until the assigned number of follow-ups is zero. Using labels in our simulation model, a rebooked appointment is carried out if patient cancels the appointment or does not attend the clinic.

Patients can be referred from outpatient to inpatient specialties according to the pathway shown in Fig. 2. Elective patients are referred to inpatient specialties and wait for their admissions according to observed frequency distributions based on age groups and type of specialty. Non-elective patients are admitted to the inpatient specialties in two main routes: mostly via the A&E department and others (i.e., GP and consultant clinic referrals). After pre-assessment, theatre process is performed, if required. Patients, who need to be admitted to a ward, stay in a bed in accordance with the observed frequency distributions regarding length of stay until discharged. On the other hand, day-case patients are discharged as they do not require a bed.

The conceptualized hospital model in Fig. 2 and the simulation model in Fig. 3 were verified by the directors (i.e., clinical directors, turnaround director and director of finance) and consultants in the hospital.

One of the virtues of our whole hospital simulation model is its ability to study the interaction between hospital specialties. The output of one specialty is an input to another specialty, that is the indigenous demand is generated by the simulation. For example, this happens between A&E and inpatient specialties in Fig. 2. If an emergency patient is to be admitted to hospital the patient is transferred to a ward inside the hospital. Similarly, an outpatient can be transferred to a ward bed. These interactions are advantageous to investigate the effects of transition rates. Using the DSS, the effects of increasing the rate of transferring A&E patients to wards can be investigated, so that necessary beds can be allocated for emergency department. Likewise, effects of referral rates from outpatient specialties to inpatient facilities can be evaluated with the model. In most hospital simulation models, patient demand is assumed to be exogenous, whereas in our model the demand is both exogenous and endogenous. With this feature, distributions used in the model are broken down to the causes which create the variation.

Another type of interaction occurs between hospital units. In the model, for example, a patient in a ward can be transferred to a different ward, or a patient who had a surgery can be taken to a ward. Such interactions between hospital units are possible in the model. Flow of patients inside the hospital gives DSS the ability to analyze the effects of different overflow rules. If all beds in the Trauma and Orthopaedics (T&O) wards are occupied, how can a bed-manager locate a bed for a T&O patient? In such a scenario, the simulation model can provide insights into the impact of implementing a bed-allocation rule, such as directing T&O patients to general surgery wards.

3.2.2.4. Key output metrics. A simulation model of this scale generates many outputs, and our model's output metrics are shown in Table 5. Among the set of outputs, the attention was on three metrics as agreed with the hospital management. We measured the performance using the following output metrics at hospital level: Demand Coverage Ratio (DCR), Bed Occupancy Rate (BOR) and Total Revenue.

Table 5
Outputs of the whole simulation model.

A&E department	Outpatient Specialty	Inpatient Specialty
• Total number of capacity • Bed occupancy rates (%) • Consultant Hours (hours) • Nurse Hours (hours) • Demand Coverage Ratio (%) • Total Revenue (£)	• Total number of first attendances • Total number of follow up attendances • Total number of DNAs • Total number of cancellations • First to follow up ratio • Total number of clinic attendance • Clinic utilization rate (%) • Consultant Hours (hours) • Demand Coverage Ratio (%) • Total Revenue (£)	• Total number of elective admissions • Total number of non-elective admissions • Total number of elective theatre procedure • Total number of non-elective theatre procedure • Elective theatre utilization rate (%) • Non-elective theatre utilization rate (%) • A&E to inpatient conversation rate (%) • Bed occupancy rates (%) • Required number of beds • Consultant Hours (hours) • Demand Coverage Ratio (%) • Total Revenue (£)

DCR is a metric proposed by Ref. [50] that was developed to measure the percentage of patients admitted to the hospital and discharged using the available resources of each specialty. Its formula is shown in Eq. (1). This output shows a hospital's ability to meet demand. For example, 100% DCR means that all patient demands are met with the available resources. Using this output metric, hospitals can better understand their performance, e.g., if DCR is below 100% (say 90%) this means that the specialty was unable to cope with the demand, thus require additional resources to treat the remaining 10%. The DCR of the hospital is computed by the formula in Eq. (1) and used in our simulation model.

$$Demand\ Coverage\ Ratio\ (\%) = 100 \times \left(\frac{AEP + \sum_{j=1}^{s_o} NPDO_j + \sum_{j=1}^{s_i} NPDI_j}{AEA + \sum_{j=1}^{s_o} NPAO_j + \sum_{j=1}^{s_i} NPAI_j} \right) \tag{1}$$

AEP is the number of patients who are discharged using available resources from the A&E department; NPDOj is the number of patients who are discharged using available resources from the outpatient specialty j; NPDIj is the number of patients who are discharged using available resources from the inpatient specialty j; AEA is the number of patients who are admitted to the A&E department; NPAOj is number of patients who are admitted to the outpatient specialty j; NPAIj is the number of patients who are admitted to inpatient specialty j; so is the total number of outpatient specialty; si is the total number of inpatient specialty.

NHS Trusts in the UK measure bed occupancy rate of the hospitals on a regular basis as a key output metric of their inpatient services. NHS Trusts measure the BOR using Eq. (2) which is a rate calculating the number of hospital beds occupied in the total number of available hospital beds in a period [72].

$$Bed\ Occupancy\ Rate\ (\%) = 100 \times \left(\frac{The\ number\ of\ occupied\ bed\ days}{Total\ number\ of\ beds \times Number\ of\ days\ in\ the\ period} \right) \tag{2}$$

Financial output is one of the most important key metrics for strategic planning purposes. Total revenue is measured in our simulation study as one of the outputs using the formula shown in Eq. (3). This output consists of the following sources of revenue: A&E department, outpatient, and inpatient specialties. At this point, the Market Forces

Factor (MFF) is used as a multiplier in calculation of the revenue. The MFF indicates a reflection of service cost which might depend on the location of each hospital in the country [73]. Firstly, the portion of revenue coming from the A&E department is calculated by multiplying average revenue by total number of A&E arrivals. Secondly, an HRG Code is identified for each patient to determine the diagnostic procedures in outpatient and inpatient specialties. These codes were utilized in calculating total revenue for outpatient (first and follow up treatment) and inpatient (for elective and non-elective admissions). For example, the hospital reimburses £80 (£92 with the MFF) for an HRG Code "FZ57Z - Diagnostic or Therapeutic Rigid Sigmoidoscopy 19 years and over". This code is assigned to a patient who attends general surgery outpatient clinic as a first referral.

The revenue for an inpatient specialty is calculated differently compared to A&E and outpatient specialties. The revenue depends on patients' length of stay in a bed. A long stay payment for days exceeding the trim point is applied by considering the trim point determined by the NHS. Trimpoint is a threshold for the length of stay for patients [74]. For example, non-elective long stay trimpoint is 5 days for a HRG Code which is EB01Z (Non-Interventional Acquired Cardiac Conditions) in the general surgery inpatient specialty and £211 (£243 with the MFF) per day for exceeding the trimpoint is charged, whereas non-elective spell tariff is £585 (£675 with the MFF). The hospital reimburses £1161 (MFF x £585 + MFF x 2 days x £211) if a non-elective patient with the HRG code "EB01Z" stays in a bed for 7 days.

$$Total\,Revenue\,(£) = MFF \times \left((AExRAE) + \left(\sum_{i=1}^{s_o} \sum_{j=1}^{f_j} RF_{ji} + \sum_{j=1}^{s_o} \sum_{j=1}^{fup_j} RFUP_{ji} \right) + \left(\sum_{i=1}^{s_e} \sum_{j=1}^{e_j} (TE_{ji} + TAE_{ji}) + \sum_{i=1}^{s_{ne}} \sum_{j=1}^{ne_j} (TNE_{ji} + TANE_{ji}) \right) \right) \quad (3)$$

AE: Total number of A&E arrivals; RAE: Average revenue per A&E patient; f_j: Total number of first attendance and DNAs at outpatient specialty j; RF_{ii}: i. tariff for first attendance and DNAs at outpatient specialty j; fup_{ji}: Total number of follow up attendance and DNAs at outpatient specialty j; $RFUP_{ii}$: i. tariff for follow up attendance and DNAs at outpatient specialty j; so: Total number of outpatient specialty; s_e: Total number of inpatient elective specialty; s_{ne}: Total number of inpatient non-elective specialty; e_j: Total number of admission at inpatient elective specialty j; n_{ej}: Total number of admissions at inpatient non-elective specialty j; TE_{ji}: i. tariff at inpatient elective specialty j; TAE_{ji}: i. tariff adjustment at inpatient elective specialty j; TNE_{ji}: i. tariff at inpatient non-elective specialty j; $TANE_{ji}$: i. tariff adjustment at inpatient non-elective specialty j; MFF: Market forces factor.

3.2.2.5. Verification and validation. We conducted two types of validation, black-box and white-box, to confirm the accuracy of our simulation model. Face validity was also checked during this process. We collaborated closely with key stakeholders from the hospital during the development of the model and incorporated their feedback to make improvements. We rigorously tested each unit of the model for extreme conditions and logical consequences. Based on the results, we determined that the model successfully passed the white-box validation tests. In the final demonstration, which focused on face validity, the project owners were convinced that the model is suitable for further use. Black-box validation assumes that the simulation model will behave similarly to the real system when provided with the same inputs. The output variables we measured in the simulation and observed in the real system included DCR, bed occupancy rates, and total revenue. In Table 6, the data column represents the real system's output, while the next column shows the simulation results. Since the simulation model is stochastic, its output is a random variable and comes with confidence intervals. Based on these figures, we can conclude that the simulation model accurately mimics the behavior of the real system.

Table 6
Validation of the simulation model.

Output parameters	Data	Simulation results (95% LCI, UCI)	Deviation	Percentage (%)
Demand coverage ratio (%)	99.71%	99.68% (99.38%, 99.98%)	−0.03% (−0.33, 0.27)	−0.03% (−0.33%, 0.27%)
Bed occupancy rate (%)	71.96%	73.15% (70.91%, 75.43%)	1.19% (−1.05, 3.47)	1.65% (−1.46%, 4.82%)
Total revenue (£)	£162.80 m	£161.19 m (£159.40 m, £162.98 m)	−1.61 m (−3.40 m, 0.18 m)	−0.99% (−2.09%, 0.11%)

Where LCI: Lower value of confidence interval, UCI: Upper value of confidence interval.

The simulation model was validated for each of the key output metrics shown in Table 6 for all specialties. The validation results for one of the critical metrics (i.e., length of stay and) were given in Appendix F.

3.2.2.6. Scenario analysis and experimental design. The whole hospital simulation model has many inputs and outputs and therefore it was difficult to design the experiments. Discussions with the hospital management made it clear that the hospital is expecting the number of patients to increase in the upcoming years, and in return the management wants to know its effects. Therefore, we decided to investigate the effects of increase in patient demand on revenue and level of service provision. Level of service provision is measured by two metrics, DCR and BOR. The two metrics are interrelated, however DCR enables us to assess the hospital in terms of providing healthcare to its surrounding population, and BOR measures the performance of the hospital management with regards to managing its bed capacity. The revenue, on the other hand, is a function of patient mix and number of patients. The increase in numbers does not necessarily mean an increase in revenue since different tariffs are applied to patients.

In response to the hospital management's concerns about rising demand, we developed 16 scenarios to study the impact of increased patient arrivals at three different levels. We worked on four factors: A&E admissions (A), elective inpatient admissions (B), non-elective inpatient admissions (C), and outpatient clinic attendances (D). For each factor, we applied 5% and 10% increases which created $2^4 = 16$, experiments. The two-factor experiment is essential to understand the interaction effects between the factors and convenient for exploration purposes. In addition to the two-factor analysis, we created 2 more scenarios to understand the effects of 15% and 20% increase in inpatient demand when there is 10% increase in the A&E department and outpatients. We run the simulation model for 10 replications with 5-months warm up period and the results are shown in Table 7.

4. Results and discussion

As the management of the hospital is interested in investigating the effects of an increase in patient demand on DCR, BOR, and revenue, we designed our experiments accordingly. Although the DSS is able to answer many questions, such as the number of beds configuration, we focused on demand-based scenarios. The structure of the scenarios, experimental design, and responses for key output metrics (total revenue, DCR and BOR) are given in Table 7.

The baseline model is established using predicted hospital demands as input into our simulation model. According to the baseline model, approximately £164 million revenue is expected from patient care with 97.20% DCR and around 75% BOR next year. The model predicts that the hospital will not be able to meet 3% of all demand. The reasons for not meeting the 3% demand will be clearly understood when the DCR's of each specialty are examined in greater detail, and whether it is due to

Table 7
Scenario analysis, experimental design, and results at 95% confidence interval.

Experiments		Factors				Outputs		
		A&E	Elective	Non-Elective	Outpatient	Total revenue (£)	DCR (%)	BOR (%)
Baseline model (forecasting)		0	0	0	0	164.37 m (162.55 m, 166.19 m)	97.20 (96.83, 97.57)	74.97 (72.72, 77.22)
Levels	E1	5	5	5	5	171.30 m (169.40 m, 173.20 m)	96.11 (95.75, 96.47)	78.07 (75.73, 80.41)
	E2	5	5	5	10	172.39 m (170.48 m, 174.30 m)	95.17 (94.81, 95.53)	78.05 (75.71, 80.39)
	E3	5	5	10	5	172.77 m (170.85 m, 174.69 m)	95.97 (95.62, 96.31)	79.29 (76.91, 81.67)
	E4	5	5	10	10	173.95 m (172.02 m, 175.88 m)	95.17 (94.85, 95.49)	79.30 (76.92, 81.70)
	E5	5	10	5	5	173.25 m (171.33 m, 175.17 m)	96.18 (95.84, 96.52)	78.37 (76.41, 80.33)
	E6	5	10	5	10	174.52 m (172.58 m, 176.46 m)	95.22 (94.88, 95.56)	78.36 (75.85, 80.87)
	E7	5	10	10	5	174.73 m (172.79 m, 176.67 m)	96.05 (95.69, 96.41)	79.54 (77.15, 81.93)
	E8	5	10	10	10	175.92 m (173.97 m, 177.87 m)	95.14 (94.80, 95.48)	79.60 (77.21, 81.99)
	E9	10	5	5	5	173.67 m (171.74 m, 175.60 m)	95.96 (95.60, 96.32)	80.02 (77.62, 82.42)
	E10	10	5	5	10	174.75 m (172.81 m, 176.69 m)	95.06 (94.72, 95.40)	80.04 (77.64, 82.44)
	E11	10	5	10	5	175.13 m (173.19 m, 177.07 m)	95.81 (95.44, 96.18)	81.36 (78.92, 83.80)
	E12	10	5	10	10	176.27 m (174.31 m, 178.23 m)	94.91 (94.59, 95.23)	81.20 (78.76, 83.64)
	E13	10	10	5	5	175.55 m (173.60 m, 177.50 m)	95.98 (95.64, 96.32)	80.20 (77.79, 82.61)
	E14	10	10	5	10	176.79 m (174.83 m, 178.75 m)	95.17 (94.82, 95.52)	80.25 (77.84, 82.66)
	E15	10	10	10	5	177.03 m (175.06 m, 179.00 m)	95.98 (95.67, 96.29)	81.41 (78.97, 83.85)
	E16	10	10	10	10	178.25 m (176.21 m, 180.23 m)	95.04 (94.72, 95.36)	81.43 (78.99, 83.87)
Experiment 17		10	15	15	10	181.75 m (179.73 m, 183.77 m)	94.83 (94.48, 95.18)	83.26 (80.76, 85.76)
Experiment 18		10	20	20	10	185.15 m (183.09 m, 187.21 m)	94.73 (94.44, 95.02)	84.83 (82.29, 87.37)

lack of resources. At this point, available clinic slots in some outpatient specialties will be insufficient and then the clinic utilization of those outpatient specialties will be at maximum level (100%). In addition, the number of beds in some inpatient specialties will be inadequate even if the bed occupancy rate of the hospital is less than 100% so that further investigation reveals that there exists a bed reallocation problem as seen in Table 8.

The hospital solves the overcapacity problems experienced in a few inpatient specialties by transferring patients of fully occupied inpatient specialties to beds of an unoccupied one. In the case of 10% demand increase, the bed occupancy rate will be under the target level of 85%. Experiment 17 and 18 clearly showed that the hospital has the capacity to admit 10% more patients to beds and thus, it could increase revenue. We would normally expect the DCR to increase (due to availability of beds), however a decrease on this instance means that the beds are not allocated efficiently (as it is occupied less than 85% of the time).

4.1. Demand coverage ratio

Normal plots of the effects for key output metrics are shown in Fig. 4 as experimental analysis results. In a normal plot of the effects, the further that a factor is away from the line, the greater its effect. The effects, which are located along the line are insignificant [75].

Factors which affect the demand coverage ratio are the main effects of outpatient (D), A&E (A) and non-elective admissions (C) (in the order of the effects). Outpatient arrivals are the most important hospital demand affecting the DCR. It is understood that the available capacity of outpatient specialties will not be able to meet the possible unexpected demand increase so that the DCR decreases as the Outpatient attendances increase. This result also shows that DCR is significantly affected by the first point of patient contact with hospitals, which is outpatient clinics.

Table 8
Number of beds and bed occupancy rates for the projected year (i.e., baseline model).

Specialty	Number of beds	Bed occupancy rate (%)
General surgery	88	56.07 (54.48, 57.65)
Trauma & orthopedics	59	76.60 (75.06, 78.14)
General medicine	85	106.75 (105.71, 107.78)
Cardiology	25	97.23 (94.63, 99.82)
Pediatrics	16	116.55 (111.49, 121.60)
Geriatric medicine	111	126.90 (125.33, 128.46)
Obstetrics	41	78.28 (77.67, 78.87)
Gynecology	41	31.54 (30.88, 32.19)
Others	91	16.70 (16.17, 17.23)

4.2. Bed occupancy rate

Factors which affect the bed occupancy rate are the main effects of A, C and B (in the order of the effects). The effect of outpatient attendances is negligible on bed occupancy rates. BOR is most affected by patients admitted via the A&E department. Non-elective admissions are more important than elective admissions in the increase of BOR when types of inpatient arrivals are investigated. In conclusion, BOR is mostly influenced by the changes in number of emergency patient arrivals (A&E and non-elective).

4.3. Total revenue

Factors which affect the total revenue are the main effects of A, B, C and D, and B-D interaction (in the order of the effects). The fluctuations on total revenue are most affected by the number of patients admitted in A&E and indirectly non-elective admissions (via A&E department). The effects of inpatient admissions (i.e., elective and non-elective) are larger than the effect of outpatient attendances on total revenue, although the number of inpatient admissions is not as high as the number of outpatient attendances, which is the reason why revenue items on inpatient admissions (particularly non-elective) are high.

5. Conclusion

A day hardly ever passes in the UK without the NHS hitting the tabloid newspapers, with headlines such as “our NHS is dying”, “NHS in crisis”, “A&E patients hit by winter crisis”, “NHS cuts 15,000 beds in 6 years”, and “worst nurse shortage ever”. With ever increasing demand (mainly due to an ageing population), lack of resources and beds (due to severe financial cuts), coupled with the likely impact of Brexit on staffing within the NHS, it is very likely that we will continue seeing such headlines in the future.

Key decision makers are very well aware that hospital bed occupancy is near 100%. Mental health bed occupancies are no different, with patients sitting for hours in emergency departments waiting for a bed. Primary care is struggling, some patients are unable to get appointments to be seen by a General Practitioner. Social care is near breaking point with limited community places available and no budget for care packages. So, it’s time to do things differently because the current status quo is not an option.

As such, clear and robust, long term hospital level models are

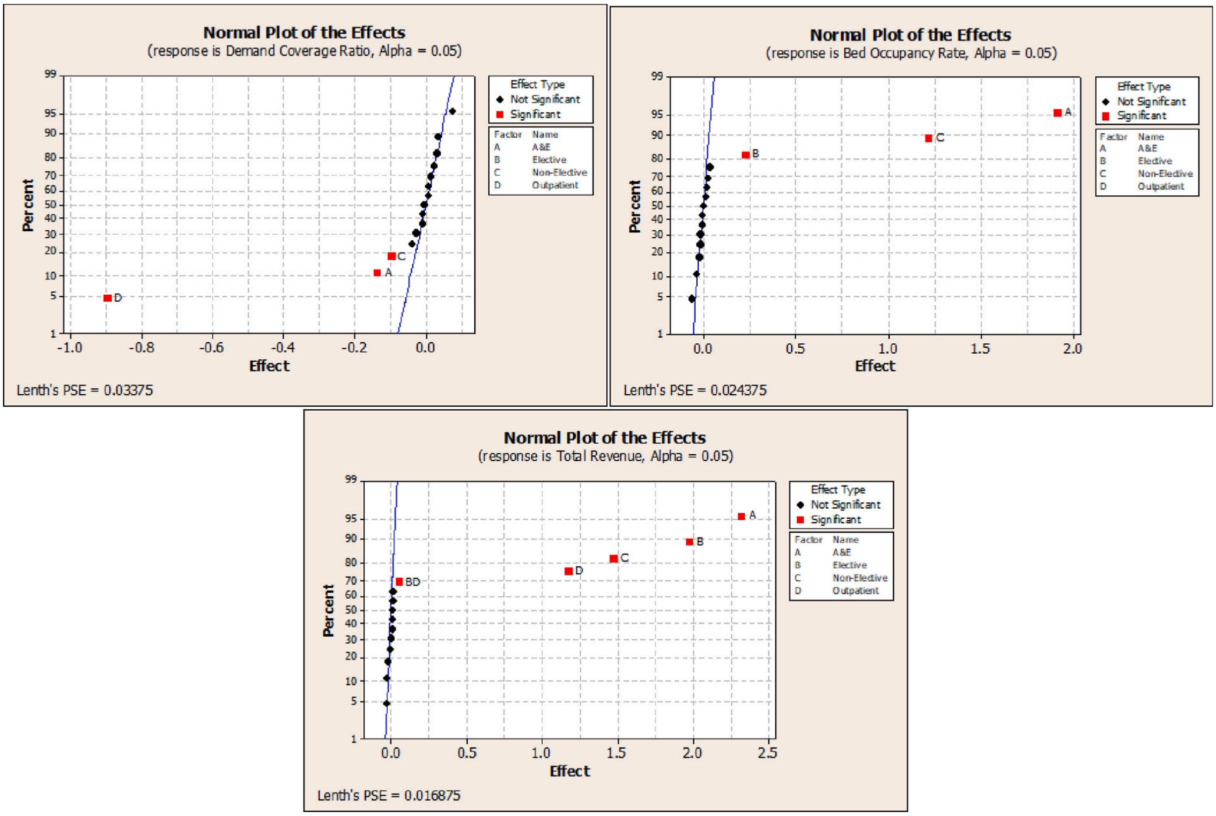

Fig. 4. Graphs of normal plot of the effect in the experimental analysis for each output metric.
Where A: A&E arrival, B: Elective admission, C: Non-elective admission and D: Outpatient attendance.

required to assess and respond to the needs of local populations, both currently and in the future. This may sound like a cliché statement, but we genuinely need models that integrate every component of a hospital to find efficient and effective use of scarce resources. Each and every department, ward, specialties and services are interconnected. An individual service cannot be assumed to be independent.

After an extensive review of the literature, we noticed that there is a gap waiting to be filled in research and academic terms, and an urgent need for a whole hospital level simulation model for the management of hospitals. We therefore developed a model in a way that has never been tackled before, linking each and every service and specialty within A&E, outpatient and inpatient services.

A vast amount of data analysis was carried out using local data and the hospital episodes statistics dataset. In total, 760 forecasting models were developed for the 31 outpatient and inpatient specialties broken down by age group. We further established approximately 600 observed frequency distributions for the simulation model.

This study shows that the hospital can cope with the increasing demand (as forecasted) with its current level of resources. Results of the simulation scenarios revealed that when the demand in A&E and outpatients increase by 10%, and elective and non-elective inpatients increase by 20%, the DCR will remain almost the same, and the BOR will increase by 10% reaching almost to the national bed occupancy target of 85%. Furthermore, with the increase in patient volumes, the revenue generated will increase by almost 13%. This study shows the gradual increase in BOR and revenue by the stepwise percentage of increments in demands. The results help hospital managements clearly see the effects of demand changes to the performance.

Furthermore, interrelationships between emergency, inpatient, and outpatients are investigated with the DSS. Simulation output analysis revealed that DCR is significantly affected by number of outpatients, and the main driver of BOR is emergency, and hence, unplanned patients. This result suggests that hospitals must concentrate on emergency patients to better utilize their bed resources. Efficient use of beds is only possible when emergency patients are managed better.

The DSS in this study also demonstrates that generic and nation-wide data sources are sufficient for analysis and modelling at hospitals. As in the UK, data repositories, like HES, should be maintained and made available to do routine analysis and create models for analysis. Artificial Intelligence (AI) algorithms can help human decisions in such automated evaluations.

The proposed DSS will provide many benefits to the management of hospitals. It will enable them to foresee patient demands for their hospitals in future years and test whether these demands are met with their available resources (using the key outputs generated from the model). In addition, the management will be able to observe how possible changes in resources (e.g. staffs, beds, rooms) affect the performance of hospitals in the safety of a simulation environment. Note that the management could easily test the system not just for one part of the hospital but to all services. For instance, at the time of developing this model, a nearby hospital's services were closing. The model was tested for scenarios where the hospital would incur an increase of 5–10% in outpatient attendance and inpatient admissions across all 31 specialties and examined whether the hospital was able to cope with this level of demand. These results will bring a different perspective to the management of the NHS for short- and long-term strategic planning, which will enable them to make rational and realistic plans.

The DSS further enables the management to assess the needs of the hospital in terms of human resources, department expansion or reduction, and medical equipment/bed requirements. Effective personnel planning prevents overemployment in hospitals, and department expansion (or reduction) readjusts bed capacity according to demands periodically and thus idle capacity (or lack of capacity) is avoided.

The whole hospital level simulation model can become a crucial instrument for key decision makers towards becoming an efficient and cost-effective service for NHS Trusts across the UK. Savings as a result of using the DSS may enable the hospital to allocate additional funds for scientific research, training of staff, and sponsorships of research students. The NHS will be able to extend their vision and maintain a sustainable service for now and into the future.

This study has produced a crucial and a practical decision support tool to help patients, taxpayers, managements of hospitals, the NHS and beyond. The tool has been utilized by senior management of a mid-size NHS Trust in England.

Note that there are wide range of forecasting models that can easily be implemented in addition to the methods we have used in this study. For instance, advanced techniques such as singular spectrum analysis, deep learning for time series forecasting, and neural networks. The contribution of this study is not around time series analysis in healthcare, this is a well-established area, but to highlight the importance of forecasting demand within a simulation study particularly at this scale. It is vital to ensure that the arrival of patients into the simulation at the specialty level within inpatient and outpatient services are reliable.

This study has some limitations. For example, patient demand in a hospital varies according to the specialty. The demand for an outpatient clinic may be low whereas an A&E demand is high. In the study, patient demand was forecasted by using only the number of patients. Instead, a much-detailed forecasting studies could have been carried out for each specialty by taking into account demographic characteristics such as age/gender. Furthermore, only four different forecasting methods commonly used in the literature were used. Along with these methods, the current forecasting methods (i.e., deep learning) could have been included in the study. Considering the operational complexity of an entire hospital, a high-level hospital simulation model was developed. By modelling each specialty at the tactical level, operational scenarios can measure critical performance outcomes for each specialty. All these limitations can be taken into account in future studies. In addition, the study revealed a reallocation problem/opportunity regarding the available number of beds in the hospital. We will consider this issue of the hospital in a future study using simulation modelling. Further study will integrate the optimization modelling with the whole hospital simulation model in order to optimally reallocate the available number of beds by taking into account a number of constraints related to the hospital.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Input Parameters of the Simulation Model for the Accident and Emergency Department

Input parameters	Estimates	Distributions	References
Patient inputs	Theoretical distribution	Theoretical distribution	HES dataset
- Available demand (2012/13)	Theoretical distribution	Theoretical distribution	N/A
- Forecasted year (2013/14)			
Physical inputs	22	Fixed	Local data
- Number of beds	5	Fixed	Local data
- Number of triage rooms	4	Fixed	Local data
- Number of clinic rooms			
Staff inputs	12	Fixed	Local data
- Number of doctors	21	Fixed	Local data
- Number of nurses			
Financial inputs	(2012/13–2013/14)	Fixed	[77]
Revenues in the A&E:	£114 - £124		
- Average revenue of treatment per a patient			
Other inputs	47%	Multinomial	HES dataset
Demographic features:	53%	Multinomial	HES dataset
- Gender	23%	Multinomial	HES dataset
1. Male	28%	Multinomial	HES dataset
2. Female	16%	Multinomial	HES dataset
- Age groups	12%	Multinomial	HES dataset
1. Age group 1 (0–15)	21%	Multinomial	HES dataset
2. Age group 2 (16–35)	76%	Multinomial	HES dataset
3. Age group 3 (36–50)	24%	Multinomial	HES dataset
4. Age group 4 (51–65)	First test-Second test-Third test	Multinomial	HES dataset
5. Age group 5 (65+)	42%–8% - 12%	Multinomial	HES dataset
Laboratory process:	13%–22% - 10%	Multinomial	HES dataset
- Laboratory service	31%–26% - 26%	Multinomial	HES dataset
1. What percentage of patients are referred to the laboratory?	1%–32% - 27%	Multinomial	HES dataset
2. What percentage of patients are not referred to the laboratory?	8%–7% - 16%	Fixed	Local data
- Percentage of laboratory tests	5%–5% - 9%	Average	Expert Opinion
X-Ray	3	Average	Expert Opinion
Electrocardiogram	15 min	Frequency distribution	HES dataset
Haematology	10 min	Frequency distribution	HES dataset
Biochemistry	Frequency distribution	Frequency distribution	HES dataset
Urinalysis	Frequency distribution		
Others	Frequency distribution		
Shifts			
Distributions			
- Waiting time for pre-assessment			
- Pre-assessment process			
- Time for treatment			
- Treatment time			
- Time for discharge			

Where HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service.

Appendix B. Input Parameters of the Simulation Model for the Trauma & Orthopaedics Outpatient Specialties

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of attendances for the available period (2012/13)	N/A	HES dataset
Trauma & orthopaedics (First referral)	- Number of attendances from the forecasting method for the projected period (2013/14)	N/A	N/A
Trauma & orthopaedics (Follow up referral)			
Financial inputs	(2012/13–2013/14)	Frequency distribution	Department of Health and Social Care (2013)
Revenue:	Frequency distribution		
- Trauma & orthopaedics	Frequency distribution	Frequency distribution	
1. Average first attendance tariff			
2. Average follow up attendance tariff			
Other inputs	(First referral – Follow up referral)	Multinomial	HES dataset
Demographic features:	19%–18%	Multinomial	HES dataset
- Age groups	18%–18%	Multinomial	HES dataset
1. Age group 1 (0–15)	19%–19%	Multinomial	HES dataset
2. Age group 2 (16–35)	21%–21%	Multinomial	HES dataset
3. Age group 3 (36–50)	23%–24%	Frequency distribution	HES dataset
4. Age group 4 (51–65)	Frequency distribution		HES dataset
5. Age group 5 (65+)	Frequency distribution	Frequency distribution	HES dataset
Distributions:	Frequency distribution		Local data
- Waiting time for first appointment	36,700	Frequency distribution	
- Follow up number			
- Length of period for follow up treatment		Fixed	
Total available outpatient clinic slots (per *year):*			
- Trauma & orthopaedics			

Where HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service.

Appendix C. Input Parameters of the Simulation Model for the Trauma & Orthopaedics Inpatient Specialties

Input parameters	Estimates	Distributions	References
Patient inputs	- Daily number of admissions for the available period (2012/13)	N/A	HES dataset
Trauma & orthopaedics (Elective)		N/A	N/A
Trauma & orthopaedics (Non-elective)	- Number of admissions from the forecasting method for the projected period (2013/14)		
Financial inputs	(2012/13–2013/14)	Frequency distribution	Department of Health and Social Care (2013)
Revenue:	Frequency distribution		
- Trauma & orthopaedics	Frequency distribution	Frequency distribution	
1. Elective tariff			
2. Non-elective tariff			
Physical inputs	59	Fixed	Local data
Number of beds			
Other inputs	(Elective – Non-elective)	Multinomial	HES dataset
Demographic features:	3%–0%	Multinomial	HES dataset
- Age groups	12%–10%	Multinomial	HES dataset
1. Age group 1 (0–15)	20%–14%	Multinomial	HES dataset
2. Age group 2 (16–35)	30%–20%	Multinomial	HES dataset
3. Age group 3 (36–50)	35%–56%	Frequency distribution	HES dataset
4. Age group 4 (51–65)	Frequency distribution		HES dataset
5. Age group 5 (65+)	Frequency distribution	Frequency distribution	
Distributions:			
- Waiting time for first admission			
- Length of stay			
Theatre inputs	8024	Fixed	Local data
- Total number of theatre procedure annual capacity	3011	Fixed	Local data
	93%	Multinomial	Local data
1. Trauma & orthopaedics (Elective)	90%	Multinomial	Local data
2. Trauma & orthopaedics (Non-elective)			
- What percentage of inpatient admissions end up having a surgery?			
1. Trauma & orthopaedics (Elective)			
2. Trauma & orthopaedics (Non-elective)			

Where HES: Hospital episodes statistics, N/A: Not available, NHS: National Health Service.

Appendix D. Forecasting Results for the Outpatient Specialties

Specialities	First referral		Follow up referral	
	Forecasting Model	Forecasting Period	Forecasting Model	Forecasting Period
General Surgery	SLR	Daily	SLR	Daily
Urology	SLR	Daily	SLR	Daily
Trauma & Orthopaedics	SLR	Daily	STLF: STL + ETS(A,N,N)	Daily
Ear, Nose and Throat (ENT)	SLR	Daily	ARIMA (1,1,3)	Daily
Ophthalmology	ES: ETS(A,N,N)	Daily	ES: ETS(A,N,N)	Daily
Oral Surgery	ES: ETS(M,N,N)	Monthly	STLF: STL + ETS(A,N,N)	Monthly
Anaesthetics	SLR	Daily	SLR	Daily
General Medicine	SLR	Daily	ARIMA (0,1,1)	Weekly
Gastroenterology	STLF: STL + ETS(A,N,N)	Daily	ES: ETS(A,N,N)	Daily
Clinical Haematology	SLR	Daily	SLR	Daily
Cardiology	SLR	Daily	SLR	Monthly
Dermatology	STLF: STL + ETS(A,N,N)	Daily	ES: ETS(M,N,N)	Weekly
Neurology	STLF: STL + ETS(M,N,N)	Monthly	ARIMA (5,1,0)	Daily
Rheumatology	SLR	Daily	SLR	Daily
Paediatrics	SLR	Daily	ARIMA (5,1,3)	Daily
Obstetrics	STLF: STL + ETS(A,N,N)	Monthly	ES: ETS(M,A,N)	Monthly
Gynaecology	SLR	Daily	SLR	Daily
Clinical Oncology	ARIMA (4,0,0)	Weekly	ARIMA (0,1,1)	Weekly
Others	ES: ETS(M,A_d,N)	Monthly	ARIMA (0,1,1)	Monthly

Where ARIMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise linear regression, STLF: The function of the seasonal and trend decomposition method.

Appendix E. Forecasting Results for the Inpatient Specialties

Specialities	Elective		Non-elective	
	Forecasting Model	Forecasting Period	Forecasting Model	Forecasting Period
General Surgery	SLR	Daily	ARIMA (0,1,1)	Daily
Urology	ES: ETS(M,A_d,N)	Weekly	–	–
Trauma & Orthopaedics	ARIMA (2,1,3)	Daily	ARIMA (0,1,1)	Weekly
Ear, Nose and Throat (ENT)	SLR	Daily	–	–
Ophthalmology	ARIMA (0,1,0)	Monthly	–	–
Oral Surgery	SLR	Daily	–	–
General Medicine	ES: ETS(M,A,N)	Monthly	STLF: STL + ETS(A,N,N)	Monthly
Gastroenterology	SLR	Daily	–	–
Clinical Haematology	SLR	Weekly	–	–
Cardiology	SLR	Daily	ES: ETS(A,N,N)	Monthly
Medical Oncology	SLR	Daily	–	–
Paediatrics	ARIMA (0,1,3)	Weekly	ARIMA (1,1,1)	Daily
Geriatric Medicine	–	–	ARIMA (0,1,2)	Daily
Obstetrics	–	–	ARIMA (0,1,1)	Daily
Gynaecology	ARIMA (1,0,0)	Monthly	SLR	Monthly
Clinical Oncology	SLR	Daily	–	–
Radiology	ARIMA (0,1,1)	Weekly	–	–
Others	ES: ETS(M,A_d,N)	Weekly	ARIMA (0,1,1)	Daily

Where ARIpMA: Autoregressive integrated moving average, ES: Exponential smoothing, SLR: Stepwise linear regression, STLF: The function of the seasonal and trend decomposition method.

Appendix F. - Validation of the simulation model for length of stay

Type of Admission	Output parameters	Data	Simulation results (95% LCI, UCI)	Deviation	Percentage (%)
Elective Inpatient	General Surgery	1.08	1.03 (1.03, 1.04)	−0.05 (−0.05, −0.04)	−4.85 (−4.85, −3.88)
	Urology	0.40	0.40 (0.39, 0.40)	0.00 (−0.01, 0.00)	0.00 (−2.50, 0.00)
	Trauma & Orthopaedics	1.72	1.70 (1.69, 1.70)	−0.02 (−0.03, −0.02)	−1.16 (−1.74, −1.16)
	General medicine	0.33	0.32 (0.31, 0.32)	−0.01 (−0.02, −0.01)	3.03 (−6.06, −3.03)
	Cardiology	0.74	0.73 (0.72, 0.74)	−0.01 (−0.02, 0.00)	−1.35 (−2.70, 0.00)
	Paediatrics	0.94	0.96 (0.92, 1.00)	0.02 (−0.02, 0.06)	2.13 (−2.13, 6.38)
	Gynaecology	0.61	0.60 (0.60, 0.61)	−0.01 (−0.01, 0.00)	−1.64 (−1.64, 0.00)
	Others	0.90	0.94 (0.92, 0.96)	0.04 (0.02, 0.06)	4.44 (2.22, 6.67)
Non-elective Inpatient	General surgery	4.16	4.22 (4.21, 4.23)	0.06 (0.05, 0.07)	1.44 (1.20, 1.68)
	Trauma & Orthopaedics	6.78	6.88 (6.87, 6.90)	0.10 (0.09, 0.12)	1.47 (1.33, 1.77)
	General medicine	3.81	3.75 (3.74, 3.75)	−0.06 (−0.07, −0.06)	−1.57 (−1.84, −1.57)
	Cardiology	7.17	7.01 (7.00, 7.03)	−0.16 (−0.17, −0.14)	−2.23 (−2.37, −1.95)
	Paediatrics	3.51	3.52 (3.51, 3.53)	0.01 (0.00, 0.02)	0.28 (0.00, 0.57)
	Geriatric medicine	7.34	7.05 (7.04, 7.06)	−0.29 (−0.30, −0.28)	−3.95 (−4.09, −3.81)
	Obstetrics	1.49	1.57 (1.56, 1.58)	0.08 (0.07, 0.09)	5.37 (4.70, 6.04)
	Gynaecology	1.91	2.02 (2.01, 2.02)	0.11 (0.10, 0.11)	5.76 (5.24, 5.76)
	Others	4.25	4.00 (3.98, 4.01)	−0.25 (−0.27, −0.24)	−5.88 (−6.35, −5.65)

Where LCI: Lower value of confidence interval, UCI: Upper value of confidence interval.

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