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1. INTRODUCTION

1.1. Emergency Department length of stay

The relationship between demand and capacity is a major problem for hospital Emergency Departments (EDs) worldwide (Higginson et al., 2011). Difficulties in managing attendance, throughput and discharge can lead to longer stay which is associated with mortality (Mason et al., 2014), as well as unnecessary admissions, or people leaving without being seen who are at higher risk of short term adverse events (Guttmann et al., 2011).

Because of the unwanted clinical outcomes associated with delayed discharge, in 2005 the UK National Health Service mandated that 98% of patients should wait no longer than four hours from initial admission to be admitted to hospital, discharged home, or otherwise to leave the department (Mason et al., 2012a). This has since been reduced to 95%, a target which many Trusts still fail to reach, thus incurring financial penalties (Iacobucci, 2015). The arbitrariness of the target itself with respect to clinical need continues to be controversial, (Mason et al., 2012b) and its use is under review with suggestions to focus more on mean waiting times for different conditions, (NHSEngland, 2019) but it remains a surrogate marker for care quality supported by the Royal College for Emergency Medicine and has reportedly driven better access to investigations and hospital bed management (Weber et al., 2012).

Studies of ED length of stay have identified both extrinsic and intrinsic factors. Two broad extrinsic factors, which are not under the control of the ED, have been identified (Jarvis, 2016): increased attendance/ departmental occupancy (Bergs et al., 2014) and bed availability or capacity in wards to which patients may be discharged (Mahsanlar et al., 2014). Intrinsic factors include patient characteristics, for example older patients (Hosseininejad et al., 2017), those with higher acuity, (Chaou et al., 2016) and those with specific histories including hypertension or atrial fibrillation (Rashid et al., 2013) show longer length of stay. Other barriers to throughput include delayed consultant input (Hosseininejad et al., 2017) or diagnostic tests (Yoon et al., 2003). Many interventions to improve patient flow have been piloted, including, for example, triage interventions (e.g. fast track for patients with less severe symptoms; (Oredsson et al., 2011)), rapid assessment by clinicians (Bullard et al., 2012), early task initiation such as diagnostic tests ordered during the triage process (Batt and Terwiesch, 2017) and the provision of faster results for routine investigations (Oredsson et al., 2011). Despite these studies patient flow remains a challenging problem in EDs worldwide.

1.2. Resilient Health Care

Resilient Health Care (RHC) involves the application to health care of Resilience Engineering (RE), a well-developed theory of system performance which stresses how multiple aspects of organisational performance fluctuate over time, co-vary and interact (Hollnagel et al., 2006).

Managing ED patient flow has been the subject of a number of RHC studies (Nemeth, 2008; Wears et al., 2007) showing the importance and limits of adaptive actions taken by staff to compensate for surges in patient numbers. Such adaptive actions include expediting tests, allocating extra staff to overloaded areas and garnering extra resources from other areas in the hospital (Back et al., 2017).

Qualitative work has shown that managing ED patient flow is not a trivial task, (Back et al, 2017), largely because of the opacity of the system. Although electronic departmental systems produce a summary of how many patients are in the ED and their length of stay, further details that may be predictive of potential delay, such as older age, readmission status or high acuity are embedded in individual records and not easily aggregated. Other data from organisational systems, such as bed capacity or staffing are not integrated into ED systems and are difficult to relate to other demands on the system. Lack of summary information about the extent of interacting demands on the system limits the ability of the staff to monitor patient flow and adapt accordingly. RHC theory proposes that resilient performance is underpinned, in part, by the ability to monitor the work system for developing problems and to respond appropriately in enough time to manage those problems. Current ED data systems appear to be designed to support clinical tasks, but do not support well the ability to monitor the work system for dynamic sets of circumstance and optimise performance at the unit level. Clinicians have, as might be expected, developed informal means of assessing demand by, for example, departmental walk-rounds to gauge the status of different patients (dependent on being able to find the appropriate staff member to ask). Semi-formal attempts to manage patient flow included regular ‘huddles’ to monitor current conditions but these also rely substantially on who is available for input, and informal information gathering techniques (Back et al., 2017) and clinicians report varying effectiveness of such functions in offsetting potential blockages. Often, compensatory actions of staff are reduced to “firefighting” rather than pro-actively managing performance. In resilience terms this describes a system in which adaptive capacity has been exhausted and staff therefore cannot effectively pre-empt problems (Nemeth, 2008; Wears et al., 2007).

Healthcare organisations capture large amounts of data that could inform better monitoring and responding but no one person or function captures a clear system level picture of demand versus capacity. To date, RE work in Emergency Departments has focused on the ability or potential of individuals or teams to monitor variable conditions and adapt dynamically, rather than exploring the utility of the organisational monitoring systems to facilitate effective, timely response, which this paper now sets out to do. There is now a clear need to question the role of routine administrative data in RHC terms, and explore the potential of designing data management or technological interventions to enhance resilience potential through the display of dynamic system-level data.

Effective technological solutions should be based on a deep understanding of the context in which the technology operates, aligned to RE exhortations to understand Work-as-Done in practice as a basis for improvement (Wears et al., 2015). To progress this vision for system level technological support an in-depth study of the ways that demand and capacity are captured and how they relate to outcomes is required. Demand on the system should be conceptualised as encompassing more than simple patient numbers and include other patient and organisational factors that could increase demand. Demand and capacity misalignments are common and the various interactions between demand and capacity that produce good and bad performance should be quantified to support a better designed intervention for patient flow management. The relative influence of variable demands and conditions on performance can only be assessed if these are collated, screened and studied holistically, rather than isolated and studied in small sets as is usually the case.

In this paper we describe a study that integrated data from existing sources routinely collected in a healthcare organisation from the perspective of RHC, as a first step towards in depth understanding of demand and capacity. We set out to build an integrated model of system performance (in this case, for length of stay) via the multitude of interacting patient and organisational factors that are routinely monitored, with the aim of finding a core set of predictors of organisational performance that might better support proactive system monitoring and response. The dataset was organised via the Concepts for Applying Resilience Engineering model, which articulates how resilient performance is achieved through adaptive response to demand and capacity mismatches (Anderson et al., 2016), and findings are discussed in terms of Resilient Health Care theory.

1.3. Aims

The aim of this study was to test the feasibility of building an integrated dataset to support the work of the ED in monitoring system input and responding in a timely way to developments that might overwhelm the capacity of the system. This paper reports on the identification, screening, integration, and statistical analysis of routine data from various sources in the ED and the wider hospital to identify the patient and organisational variables associated with length of stay and achievement of the 4-hour target. Recommendations for improved data capture to facilitate ED system performance through adaptive response to variability are identified.

Specific objectives were:

- Identify sources of data (patient, unit, organisation) to populate the performance model
- Establish processes for data cleaning, transforming and standardising where necessary and for collecting data on an ongoing basis
- Build an integrated dataset and use statistical modelling techniques to quantify the relationships between variables in the model and identify predictors of patient throughput
- Make recommendations for evidence-based monitoring to support adaptive capacity and system response

2. METHOD

2.1. Setting

The setting for this study was a major United Kingdom NHS Foundation Trust, with two major teaching hospitals, around 15,300 staff, and a turnover of £1.5 billion. There were 2.4 million patient contacts in 2016/17, with 204,000 ED attendances ('spells', across various sites). Data apply to the main ED site, operating a conventional system of initial streaming, registration, assessment/ triage and treatment in various treatment areas. Patients presenting with minor injury or illness are routed to an Urgent Care Centre (UCC) located within the ED staffed by general medical practitioners and emergency nurse practitioners. More serious cases are seen by emergency medicine doctors or referred to other specialities.

2.2. Data sources and variables

Data were both patient level (e.g. diagnostic codes, age), and organisational (e.g. number of nurses for day and night shifts, number of patients). This created challenges for creating one dataset especially due to variable periodicity. For example, patient attendance data (basic demand) were collated daily (24 hours) whereas staffing data (basic capacity) were per shift (12 hours). Further capacity issues with equipment availability or operability can be 'present' as a data point for weeks, and bed capacity (via monitoring of occupancy) was obtained from a hospital database and was a daily measure. A measure of how busy the department was when each patient arrived was calculated from the patient-level ED dataset, using the numbers of arrivals in the last hour to the point at which the person entered the ED. Formally recorded patient safety incidents in the last 6 hours were conceptualised as creating 'load' on the system and were categorised from codified incident types as: 'security and violence' incidents; or 'all other' incidents. Data on varied responses to initial presenting conditions included triage and location decisions, and 'escalating' via specialist input. A detailed data glossary including data sources and code definitions, and a transformation log were developed to enable a co-ordinated approach to the data collection and analysis. Data were modelled using multivariable logistic regression (breach) and ordinary least squares regression (length of time). Table 1 shows a summary of the variables included in the analyses.

INSERT TABLE 1 ABOUT HERE

2.3. Statistical analysis

Data were collected for a 24-month period from April 2014 to the end of March 2016. For each outcome variable we modelled our target organisational performance outcome using the various demand, capacity and process variables as predictors.

Whether a patient breached or not at four hours was modelled using logistic regression. All independent variables were included in the model. A measure of statistical importance of each variable was calculated for each independent variable by dividing its χ^2 value by the degrees of freedom (χ^2/df). This provided an indication of the relative importance of each variable when compared against all other variables. Overall model fit was assessed using the percent concordance, defined as follows “A pair of observations with different observed responses is said to be concordant if the observation with the lower ordered response value has a lower predicted mean score than the observation with the higher ordered response value” (UCLA, 2017). Percent concordance shows the probability of the model being able to distinguish between different outcomes. Rice and Harris (Rice and Harris, 2005) provide recommendations for evaluating model goodness of fit based on measures of concordance (Excellent/very high = 0.714, Good/medium = 0.639, Fair/low = 0.556). These correspond to the large, medium and small effect sizes proposed by Cohen (Cohen, 1992). We used these thresholds to interpret our results.

Additional analyses were conducted for breaches by adding specialty input required and admission ward for patients separately to the decision to admit model to see what impact they might have. A sensitivity analysis was performed on the breach at four hours outcome to gauge how well the model fits an independent (validation) dataset. The data were split into eleven random samples: ten of almost equal size (~ two months data) for testing; and a final random sample (~ four months of data) for validation purposes. The multivariable model was fitted to each test dataset. The parameter estimates were averaged across the ten analyses and then applied to the validating dataset.

For eventual hospital admissions only (n=36,006), time from entering the ED to a request to admit, and from request to admit to discharge (to a hospital ward/unit) was modelled using ordinary least squares (LOS) regression. People entering the ED before 8th April 2014 onwards (the study period started on 1st April 2014) were excluded from the analysis because for some of those people it was not possible to determine whether they had been readmitted in the last seven days. Time from request to admit to discharge was natural logged to normalise the distribution and all values exceeding 36 hours were set to 2,160 minutes (n=78, 0.22%). Adjusted means (antilogarithm of mean log time from request to admit to discharge) with 95% confidence intervals were calculated. The semi-partial $\omega 2$ was used to measure, and rank, the contribution of each variable in the OLS regression model. If the probability of obtaining a test statistic value, assuming the null hypothesis was true, was lower than 5% this was deemed to be statistically significant.

Finally, models were refitted replacing shift with arrival hour to ascertain whether certain hours of day were prone to delay.

3. RESULTS

Figure 1 shows the probability of remaining in the ED and the rate of discharge from the ED by time.

INSERT FIGURE 1 ABOUT HERE

Just under ten percent of people experienced a breach of the four hour threshold (9.1%, n=21,196). The probability of remaining in the ED decreases rapidly as a patient's time in the ED gets closer to the four-hour point (240 minutes). Discharges peak just before the target time, and immediately fall considerably over the next 30 minutes (see discussion). The number of discharges then increases from 4 hours and 45 minutes onwards with a secondary minor peak at around six hours (a second target threshold). Factors associated with breach at four hours and the two time variables (from entering the ED to request to admit, from request to admit to discharge) are presented in Table 2, showing effect sizes ranked for each outcome.

INSERT TABLE 2 ABOUT HERE

3.1. Breaches at four hours (n=233,426)

The multivariable model shown in Table 2 had excellent concordance of 77.9%. Percent concordance for the model that included specialty was 84.2%. The corresponding measure of fit for the model that included admission ward was also excellent at 83.6%. We validated the four-hour breach model by testing the model fit using an independent validation dataset (see statistical analysis procedures section for further details). The percent concordant (AUC) from the 10 training samples ranged from 76.8% to 77.4% and for the average model fitted to the final four-month independent sample was 77.9%. This was above the excellent/very high fit threshold (≥0.714) and was the same as that obtained for the breach model fitted to all the adult ED data (77.9%).

The demand variables that had the strongest association with breach at four hours were number of people in the ED (χ^2/df =355), patients attending for readmission (χ^2/df =151), arrival mode (χ^2/df =141) and primary presenting complaint (χ^2/df =134). Process and capacity variables associated with breach included shift day/night (χ^2/df =944), first location (χ^2/df =296), triage (χ^2/df =204) and senior doctors not covered (χ^2/df =50). There was noticeable variation in outcomes utilising capacity in terms of different types of specialty input (χ^2/df =407). Compared with ED specialists, patients seeing particular specialities (coupled with different destination wards) had odds ratios for breach between 0.45(0.34-0.60) and 11.6 (9.55-14.08), with broadly higher risk of delay for higher acuity wards.

3.2. Time taken to request admission to hospital (admissions only; n=36,006)

For those people admitted to a hospital ward/unit the average time from entering the ED to a request to admit was 3.08 hours. Figure 2 shows the distribution of this variable.

INSERT FIGURE 2 ABOUT HERE

The regression model R^2 was 0.1008. Significant predictors included age ($\omega^2 = 0.0015$), shift ($\omega^2 = 0.0101$), arrival mode ($\omega^2 = 0.0044$), source of referral ($\omega^2 = 0.0083$) , triage ($\omega^2 = 0.0017$), readmission of patients ($\omega^2 = 0.0026$), primary presenting complaint ($\omega^2 = 0.0048$), first location ($\omega^2 = 0.0111$), whether the person was seen by a consultant ($\omega^2 = 0.0023$), number of people in the ED ($\omega^2 = 0.0324$), ambulance arrivals in the last hour number ($\omega^2 = 0.0011$), senior doctors not covered ($\omega^2 = 0.0025$) and day of week ($\omega^2 = 0.0024$) . All other variables had $\omega^2 < 0.001$, including gender, incidents in the last six hours, registered nurses, unregistered nurses, senior doctors not covered, junior doctors' hours covered and not covered, equipment current under repair and general bed occupancy.

3.3. Time from request to admit to discharge to a hospital ward (admissions only) (n=36,006)

For those people admitted to a hospital ward/unit it took 1.07 hours on average from request to admit to discharge. Figure 3 shows the distribution of this variable.

INSERT FIGURE 3 ABOUT HERE

A decision was taken to natural log this time variable to bring it closer to a normal distribution. The regression model R^2 was 0.0515. In demand terms the time between decision to admit and eventual admission was predicted by primary presenting complaint (ω^2 = 0.0107), source of referral (ω^2 = 0.0015), and age (ω^2 = 0.0014). As might be expected, this part of the admission pathway is also affected by various capacities (general bed occupancy: ω^2 = 0.0019; equipment under repair: ω^2 = 0.0012) and processes (first location : ω^2 = 0.0086; triage: ω^2 = 0.0022) as well as shift (ω^2 = 0.0019) and day of the week (ω^2 = 0.0010). All other variables had $\omega^2 < 0.001$. A summary of these three sets of related results is shown in Table 3 in narrative form for ease of interpretation. All odds ratios and adjusted mean times are included in supplementary material.

INSERT TABLE 3 ABOUT HERE

The size of effects remained broadly similar when shift was replaced by arrival hour (see Supplementary file 5). Number of people in ED continued to have the largest effect. Breaches were most likely to occur between midnight and 8am, and least likely to occur between 1pm and 3pm. Request to admit time mirrored the finding for breaches (longer at night) whereas subsequent discharge time was shorter during the evening and at night time (see Supplementary file 6).

4. DISCUSSION

The aims of this study were to integrate hospital datasets and model organisational performance in the emergency department based on Resilient Health Care (RHC) principles. RHC stresses the ability to monitor, respond, anticipate and learn (Hollnagel, 2018). This is important for ED patient flow management because it is not possible to respond appropriately to presentation demand without the ability to monitor for developing problems and take action before these affect care. As demand on socio-technical systems is always variable, improvement interventions should focus on supporting these abilities and therefore adaptive capacity (Anderson et al., 2016). This study is we believe the first of its kind in applying insights from Resilient Health Care to improve the use of routine hospital data to understand important outcomes in systems terms.

In summary, ED performance for adult patients was related to a complex mixture of patient and organisational variables. We have shown that a set of reliable core predictors based on triage status, re-attending patients, tracked locations, ambulance arrivals, staff issues and primary presenting complaint, amenable to timely capture, could be used to develop a parsimonious system model to support proactive decision making.

Although demand on the system, traditionally measured in terms of the number of patients in the department and hospital bed occupancy, was important, it does not fully explain variance in performance on our key outcomes. We used a model of organisational resilience to guide our selection of variables and this showed that other types of demand on the system also contributed to overall performance, including equipment failures, the occurrence of adverse incidents, ambulance arrivals in the ED, patient complexity and acuity. There was evidence that sicker patients were prioritised, but they also had longer length of stay.

Results also showed that there were longer times for decision to admit in the ED at night, for patients requiring specialist input into their care, and at weekends. These results strongly endorse the view that hospital process (for example for laboratory turnaround, elective surgical schedules, bed management, and discharge from wards), rather than ED process per se, should be the system of concern with regards to length of stay. (Magid et al., 2004) The spike in discharge shown in Figure 1 has been previously observed and discussed but can be seen as an important adaptive response. The anticipation of a 'breach' leads to discharge to meet efficiency goals. This may be at the expense of thoroughness, with the potential of increased readmission and short term adverse events (Guttmann et al., 2011). This efficiency-thoroughness trade off is a key phenomenon in resilient systems theory (Hollnagel, 2009).

Our data did not enable us to investigate this further, but interventions to optimise care processes during the night and at weekends, and the provision of enough resources at these times might improve patient flow. Specialty input could also potentially be optimised as delayed discharge was more strongly associated with some specialties, indicating that organisational factors, rather than the requirement for specialty expertise per se, are implicated.

The ability of the model to predict a breach at 4 hours remained consistent across multiple samples (percent concordance 76.8 to 77.4) and averaged model fit was confirmed on the final four-month independent sample (77.9).

4.1. Data integration for system intervention

Although hospitals produce data on a multitude of outcome variables to monitor the quality of the care they deliver, it is not integrated or available in real time, so it is difficult to monitor holistically the state of the system. Despite this clinicians and managers are tasked with managing patient flow in dynamic circumstances to facilitate throughput.

Without a holistic view of the current demands on the system and its capacity to meet them, the resilience of the system is threatened, as evidenced by the increase in proportions of patients spending over 4 hours in emergency departments in England in recent years to 12% for 2018-19 (Baker, 2019)).

The development of methods and metrics to understand and model multivariable system performance is a necessary development for optimising system performance and the quality of care. Theoretically motivated studies are relatively rare and Resilient Health Care can inform and focus modelling efforts via its coherent theories of system performance, thus helping those working in current performance focused healthcare settings.

This study is a first step towards identifying the important variables for this co-ordination activity. The key variables are number of patients in the ED, ambulance arrivals, patient age, presenting acuity and readmission status, staffing levels, missing equipment, occurrence of incidents, and general bed occupancy. These variables need to be integrated and weighted, taking into account day of the week and shift type, to allow users to ascertain quickly how likely it is that demand will overwhelm capacity and whether adaptive actions need to be taken. Such a system would require significant further development based on these initial findings.

The advantages of integrating such data include the ability to identify and plan for high-risk periods, determine the effect of different staffing configurations on care to inform planning, and identifying processes that could be optimised by organisational redesign. These results show the urgent need to move beyond simplistic monitoring of single variables to holistically monitor system performance. Hospital systems are not designed to capture the necessary data in a form that is suitable for integration, but the results of this study provide evidence of which data need to be captured by such future systems. Future work should focus on improved methods of data capture based on the exploratory analyses we have conducted. Without effective data capture the extent to which the healthcare system can monitor, learn, anticipate, and respond to challenges is limited.

4.2. Strengths and limitations

A strength of the work was that data collection, analysis and interpretation were guided by resilience potentials (Hollnagel et al., 2019) and a model of resilient performance drawn from extensive study in the ED context. (Anderson et al., 2016; Back et al., 2017) A limitation for future implementation is the time and effort required for such data integration and analysis. A detailed log of data definitions and transformations was maintained to enable interpretation of our results. The quality and availability of data, including missing data and undefined categories such as ‘other’, were also a challenge. The ‘real world’ data we were working with are uncontrolled and because there are consequences attached to target breaches data may be unreliably collected; we consulted widely with clinical partners to assist with interpretation and made informed choices but inevitably our data still contain some omissions or categories that are not completely precise or reliable. The size of the sample mitigated these problems to some extent. Single site studies are critically viewed in clinical trials and Quality Improvement but the unit of analysis here is the system rather than the patient or a single intervention being under study. Hence whilst admittedly it is not clear the extent to which the specific predictors would generalise to other hospitals and healthcare systems, the feasibility of integrating hospital data should be of wide interest even though the complex mix of predictive factors may vary across settings. Finally, as might have been expected, demand and outcome data were easier to identify and include than detailed process data on adaptive response. There are further adaptations we have identified qualitatively (for example ‘flexing’ by moving staff or equipment to cope with fluctuations in demand; (Back et al., 2017)) that are likely to provide good indicators for resilient performance if they can be captured and integrated into real time system models.

4.3. Conclusion

Hospitals produce data on a multitude of outcome variables to monitor the quality of the care they deliver. The development of theory-driven methods and metrics to understand and model multivariable system performance, rather than performance on individual variables, is a necessary development if monitoring ability is to be strengthened. The study results clearly showed the value of integrating a range of variables to enable better understanding of all the factors that affect length of ED stay.

Table 1 Summary of all variables analysed

Person level variables	**Organisational variables**	**Outcome variables**
Age (in years)	Number of people already in the ED when a patient arrives	Patient whose length of stay in the emergency department was longer than four hours: yes; no
Gender: male; female	Number of adverse incidents occurring in the last 6 hours before a patient presented	Length of time (for admitted patients) before a request to admit was made
Shift: day; night	Number of ambulance arrivals in the last hour	Length of time (for admitted patients) following a request to admit before a person was discharged from ED to another ward/unit
Arrival Mode: ambulance; public transport; foot; private transport; taxi; other	Number of registered nurses	
Source of referral: GP; self; emergency services; educational establishment; police; healthcare provider; community dental service; other	Number of nursing assistants (unregistered staff who work under supervision of a registered nurse)	
Triage: unknown; urgent; immediate resuscitation; standard; very urgent; non-urgent	Number of senior doctors (speciality trainees and consultants) not covered	
	Number of senior doctors not covered	
Primary presenting complaint (recoded): trauma; non-trauma but potentially serious; unwell; minor ailments; alcohol; mental health; unknown	Number of 'junior' doctors- provisionally registered (Foundation Year 1) and in the first year of registration (Foundation Year 2)	
	Number of junior doctors not covered	
First location: waiting area; urgent care centre (for minor ailments); majors; resuscitation; left department; unclassifiable; AAU (acute assessments ward)	Number of pieces of equipment under repair upon patient arrival	
Seen by a consultant: yes; no	General hospital wide bed occupancy: %	
Readmission within 7 days or longer: no; yes; longer	Day of the week for each patient admission: Monday; Tuesday; Wednesday; Thursday; Friday; Saturday; Sunday	

Table 2 Statistical testing of model variables with effect sizes for the three outcomes

		Breach at four hours				Time to request to admit†				Time from request to admit to discharge†			
Variable	*df*	χ^2	Pr>χ^2	χ^2/df	Rank‡	F&	Pr>F	$\omega^2_{s\text{-}p}$	Rank#	F&	Pr>F	$\omega^2_{s\text{-}p}$	Rank#
Age	18	996.8	<.0001	55.4	(8)	4.23	<.0001	0.0015	(12)	3.78	<.0001	0.0013	(7)
Gender	1	17.5	<.0001	17.5	(15)	17.97	<.0001	0.0004	(17)	6.44	.0112	0.0001	(16)
Shift	1	944.2	<.0001	944.2	(1)	405.96	<.0001	0.0101	(3)	68.42	<.0001	0.0018	(5)
Arrival Mode	5	706.8	<.0001	141.4	(6)	36.05	<.0001	0.0044	(6)	6.2	<.0001	0.0007	(10)
Source of Referral	4	114.1	<.0001	28.5	(12)	84.27	<.0001	0.0083	(4)	14.96	<.0001	0.0015	(6)
Triage	4	815	<.0001	203.8	(4)	17.7	<.0001	0.0017	(11)	21.35	<.0001	0.0022	(3)
Readmission within 7 days	2	302.7	<.0001	151.4	(5)	52.31	<.0001	0.0026	(7)	4.15	.0158	0.0002	(13)
Primary presenting complaint	6	802.4	<.0001	133.7	(7)	32.75	<.0001	0.0048	(5)	68.45	<.0001	0.0107	(2)
First location	6	1775.2	<.0001	295.9	(3)	89.44	<.0001	0.0111	(2)	85.67	<.0001	0.0112	(1)
Seen by consultant	1	9.2	.0024	9.2	(16)	92.42	<.0001	0.0023	(10)	8.12	.0044	0.0002	(14)
Number of people in ED	10	3546.1	<.0001	354.6	(2)	130.12	<.0001	0.0324	(1)	2.11	.0203	0.0003	(12)
Incidents last 6 hours (No.)	6	36.4	<.0001	6.1	(18)	2.72	.0121	0.0003	(19)	1.71	.1135	0.0001	(17)
Ambulance arrivals last hour (No.)	10	47.8	<.0001	4.8	(19)	5.41	<.0001	0.0011	(13)	1.03	.4188	0.0000	(19)
Registered nurses (No.)	10	76.3	<.0001	7.6	(17)	1.59	.1019	0.0001	(20)	3.33	.0002	0.0006	(11)
Unregistered nurses (No.)	6	17.8	.0068	3	(22)	3.51	.0018	0.0004	(18)	1.91	.0747	0.0001	(18)
Senior doctors covered (No.)	8	227.6	<.0001	28.5	(13)	13.65	<.0001	0.0025	(8)	1.95	.0489	0.0002	(15)
Senior doctors not covered (No.)	2	99.3	<.0001	49.6	(9)	18.04	<.0001	0.0009	(14)	1.82	.1614	0.0000	(20)
Junior doctor hours covered	8	34.3	<.0001	4.3	(20)	1.49	.1555	0.0001	(21)	1.09	.3691	0.0000	(21)
Junior doctors not covered (No.)	3	9.2	.0270	3.1	(21)	0.41	.7435	0.0000	(22)	0.97	.4075	0.0000	(22)
Equipment currently under repair (No.)	7	154.9	<.0001	22.1	(14)	4.21	.0001	0.0006	(15)	7.55	<.0001	0.0012	(8)
General bed occupancy (%)	6	181.1	<.0001	30.2	(11)	4.47	.0002	0.0005	(16)	13.09	<.0001	0.0019	(4)
Day of week	6	226.1	<.0001	37.7	(10)	16.73	<.0001	0.0024	(9)	16.73	<.0001	0.0024	(9)
Measures of fit													
Percent concordant		77.9											
R-Square		0.09					0.10				0.05		
Maximum rescaled R-Square		0.19											

[†] People who were admitted to a hospital ward/unit only; [‡] Rank of χ^2 /df (1=largest, 22=smallest);
[#] Rank of $\omega^2_{s\text{-}p}$ (1=largest, 22=smallest); [&] F test with [numerator degrees of freedom from *df* column, 35876 degrees of freedom in the denominator]

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Table 3 Narrative interpretation and summary of model parameter estimates†

Variable	**Breach at four hours**	**Time from entering the ED to request to admit**[1]	**Time from request to admit to discharge**[1]
Age	The chance of a breach increases with age (16: 1.00) until 70-74 (2.04) and then levels off.	Shallow inverted u-shaped relationship with shorter times for younger and older people (16 to 29: 162 to 165, 30-74: 166 to 172, 75 and over: 159 to 167)	Times are shorter for those in the 18 to 54 age range (46-49), longer for people aged 16-17(52,50) and 55 and over (51 to 56).
Gender	Males are less likely to breach than females (0.94 vs. 1.00).	Males have shorter times than females (165 vs. 168).	Males tend to be discharged sooner than females (49 vs. 51).
Shift	Breaches are more likely to occur at night compared to during the day (1.87 vs. 1.00).	Request to admit happens more quickly during the day than at night (156 vs. 177).	People are discharged more quickly at night than during the day (46 vs. 54).
Arrival Mode	You are more likely to breach if you arrive by ambulance (1.00 vs. 0.48 to 0.74).	Ambulance arrivals wait longer than other modes of arrival (180 vs. 159 to 169).	People arriving by private transport (54) and taxi (53) are discharged more slowly than by other modes (48 to 50).
Source of Referral	A person referred by a general medical practitioner is more likely to breach than other sources (1.57 vs. 1.00 to 1.25).	Times are shorter for those referred by a health care provider than by other sources (133 vs. 169 to 179).	Discharge is slower for people referred by a health care provider compared to other sources of referral (63 vs. 46 to 48)
Triage	People who are triaged to very urgent (2.07) or urgent (2.08) breach more often than other categories of triage (1.00 to 1.33).	People triaged to unknown (163), immediate resuscitation (165) and very urgent (161) have shorter times than those triaged to urgent (171) or standard (173).	People triaged as immediate resuscitation (59) or very urgent (57) are discharged more slowly than unknown (48) and urgent (47). Those categorised as standard are discharged the quickest (41).
Readmission within 7 days	Previously admitted people (within 7 days 1.15; 7 days or longer 1.35) are prone to breach more often than those who have only been admitted once.	People readmitted within the previous 7 days (158) have shorter times than those admitted only once (169) or admitted previously at least 7 days ago (172).	Those people admitted in the last 7 days are discharged more slowly (51), than those admitted at least 7 days (50) ago or only once (49) but differences are small.
Primary presenting complaint	Those who present with an unknown complaint (5.13) or with mental health problems (2.20) are more likely to breach. Those presenting with alcohol problems breach the least (0.62).	People presenting with alcohol (175) and mental health problems (186) wait longer than those presenting with other complaints (155 to 165).	People presenting with alcohol (30) and mental health problems (34) are discharged the quickest and those whose complaint is unknown the slowest (149). All other types of complaints have similar times (44 to 51).

First location	Majors (1.40) and Resuscitation (2.00) breach more often, and UCC less often (0.35), than other locations (0.82 to 1.00).	Resus (144) wait less time than other first locations (163 to 182).	Resus (69) discharge more slowly than other locations (38 to 55).
Seen by consultant	Patients not seen by a consultant are more likely to breach (1.00) than those seen (0.87).	If a person is seen by a consultant a request to admit will happen sooner (157 vs. 176).	People seen by a consultant are discharged more slowly than those not seen by a consultant (52 vs. 48)
Number of people in ED	Breaches increase as the number of people in the ED increases from 1.00 (0-9 people) to 19.47 (100 or more people).	As the number of people in the ED increases request to admit time takes longer rising from 128 (0-9 people) to 220 (100 and over).	People tend to be discharged more slowly when there are 29 or fewer (50-53), or 90 or more people still in the ED (51-55). In the 30-89 age range times are very similar (48 to 49).
Incidents last 6 hours (No.)	Breaches are higher between 3-5 incidents (1.07 to 1.20) in the last 6 hours but drop when the number reaches 6 and over (0.59)	Request to admit time fluctuates as the number of incidents increases and a linear trend is not apparent.	No significant variation
Ambulance arrivals last hour (No.)	There is a gradual upward trend in the chance of a breach, with some fluctuations	Request to admit time steadily slows as the number of ambulance arrivals increases from 161 (no ambulance arrivals) to 173 (10 or more arrivals).	No significant variation
Registered nurses (No.)	No obvious trend. The odds of a breach are highest for 23-24 nurses (1.54) and lowest for 14 (0.78) and 22 nurses (0.76).	No significant variation	Discharge times fluctuate as the number of registered nurses increases and is shorter when there are 22 nurses (36) in the ED and longest when there are 23-24 nurses (65) in the ED.
Unregistered nurses (No.)	No discernible trend, odds of a breach is highest for 6-7 unregistered nurses (1.10) and lowest for 2 unregistered nurses (0.94).	Times shorten a little once the number of unregistered nurses reaches 5 or more (0-4: 165-170, 5: 163, 6-7: 162).	No significant variation
Senior doctors covered (No.)	Breaches decrease as the number of doctors covered increases and the odds are at their lowest when 5 seniors (0.62) are covered and highest when none are covered (1.00).	A J-shaped relationship with times falling from 173 to 174 (0 to 2 doctors) to 160 (5 doctors) rising to 163 to 164 (6 or more doctors).	No significant variation

Senior doctors not covered (No.)	As the number of seniors not covered increases so does the odds of a breach (None 1.00 vs. 2-5 not covered 1.41).	Request to admit happens sooner when no senior doctors need to be covered compared to one or more (162 vs. 168 to 169).	No significant variation.
Junior doctors hours covered	Breaches occur more often beyond 30 hours (1.17 to 1.56) than below 30 hours (0.91 to 1.00).	No significant variation.	No significant variation.
Junior doctors not covered (No.)	The odds of a breach decreases from 1.00 (no junior doctors covered) to 0.85 (3 to 5 junior doctors covered).	No significant variation.	No significant variation.
Equipment currently under repair (No.)	The odds of a breach are higher when there are 7 or more equipment repairs compared with 6 or fewer (1.49 vs. 0.75 to 1.00).	Times lengthen when there are 7 or more repairs compared to 6 or fewer (175 vs. 160 to 169).	Discharge time is longer when there are 2 (52), 3 (53) or 7 or more repairs (57), and similar for all other numbers of repairs (46 to 49).
General bed occupancy (%)	The odds of a breach are highest when bed occupancy is 85% or over (85.00-89.99: 1.39, 90.00 and over: 1.67).	Request to admit happens more quickly when general bed occupancy is below 70% compared with 70% or over (161 vs. 167 to 171).	General bed occupancy has a U-shaped relationship with discharge times shortening from 52 (60.00-69.99%) to 47 (75.00-79.99%) rising to 57 (90.00 and over).
Day of week	The odds of a breach are lower on Monday (0.78), Tuesday (0.81) and Wednesday (0.83) compared to other days of the week (0.98 to 1.16).	Times are slower at weekends (Saturday 174, Sunday 172) and Thursday (168) compared to other days of the week (161 to 164).	Discharge happens sooner on Sunday than any other day of the week (45 vs. 48 to 54).

[1] Confined to people who were admitted to Hospital [†] Odds Ratios and adjusted means found in supplementary files

Ross, A. J., Murrells, T., Kirby, T., Jaye, P., & Anderson, J. E. (2019). An integrated statistical model of Emergency Department length of stay informed by Resilient Health Care principles. *Safety Science*, *120*, 129-136.

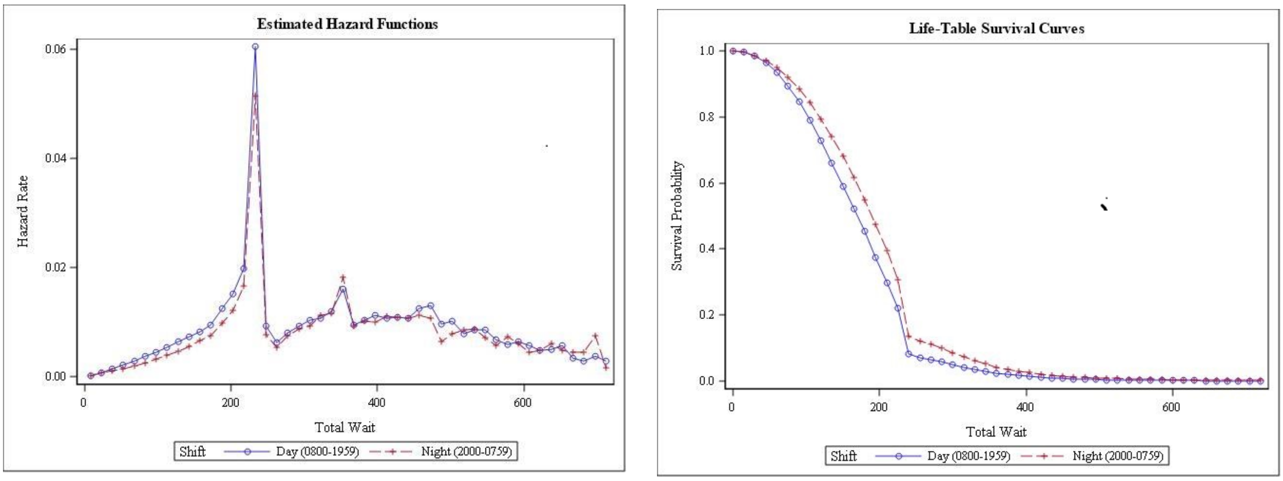

Figure 1 Time in ED (survival probability) and rate of ED discharge (hazard rate) for day and night shift over time in minutes (May 14- April 16; n = 232,920)

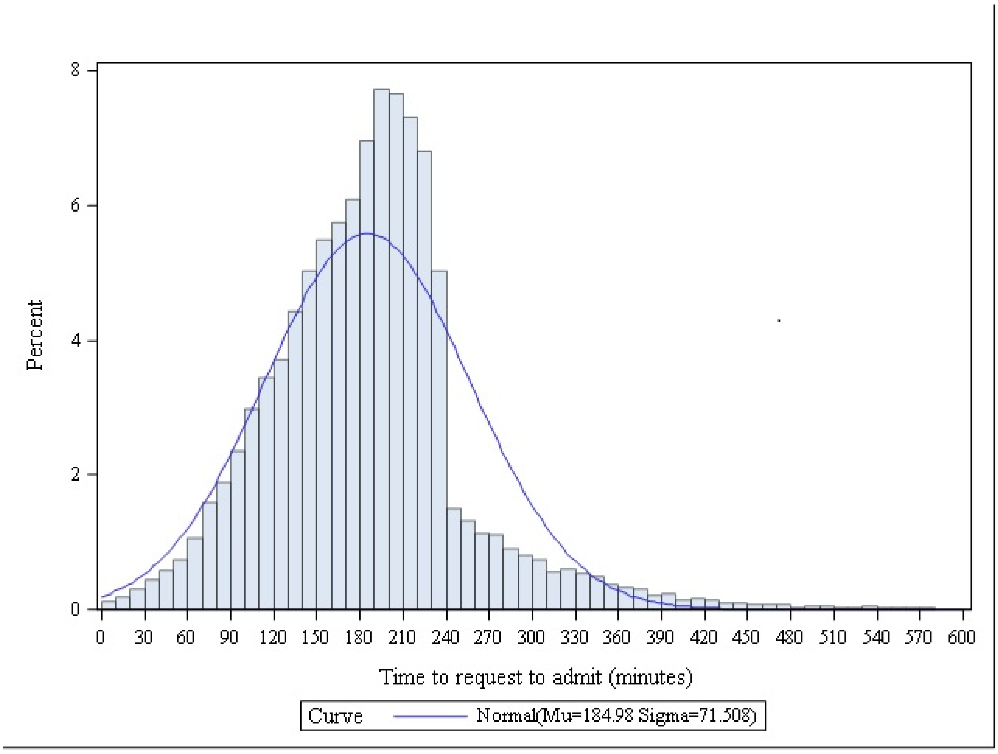

Figure 2 Time taken from entering the ED to a request to be admitted to a hospital ward

Footnote: x-axis truncated to 600 minutes

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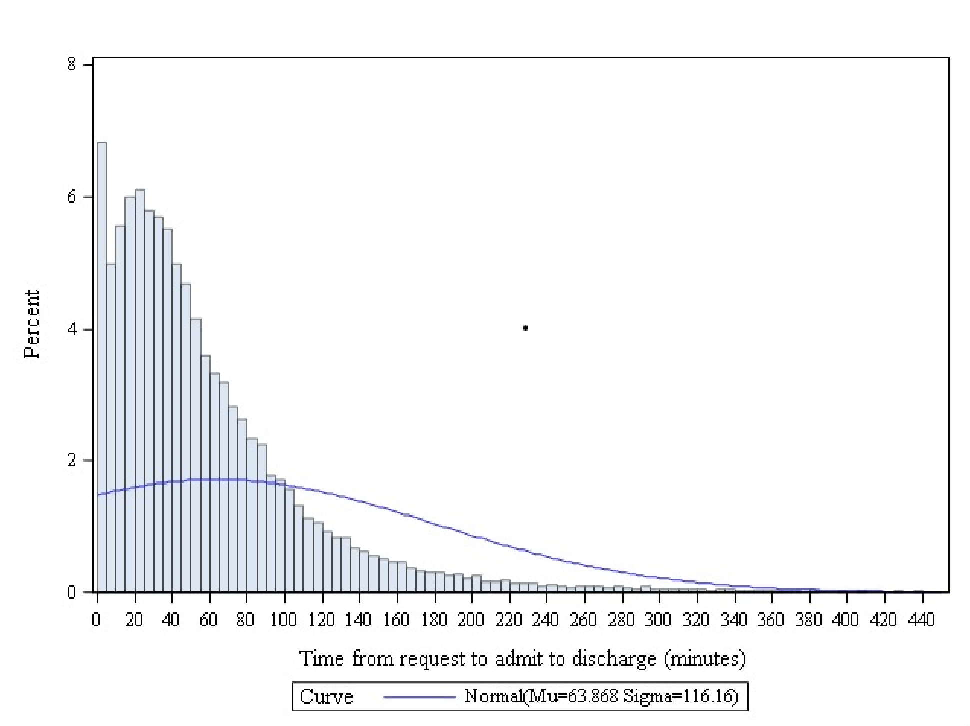

Figure 3 Time from request to admit to discharge to a hospital ward

Footnote: x-axis truncated to 450 minutes

Ross, A. J., Murrells, T., Kirby, T., Jaye, P., & Anderson, J. E. (2019). An integrated statistical model of Emergency Department length of stay informed by Resilient Health Care principles. *Safety Science*, *120*, 129-136.

SUPPLEMENTARY FILE CAPTIONS

Supplementary file 1 Descriptive statistics for modelled variables

Supplementary file 2 Odds Ratios for breach at four hours

Supplementary file 3 Adjusted means for time from entering the ED to request to admit

Supplementary file 4 Adjusted means for time from request to admit to an admission to a hospital ward (discharge)

Supplementary file 5 Statistical testing of model variables with effect sizes for the three outcomes (shift replaced by arrival hour)

Supplementary file 6 Odds ratios for breach at 4 hours, adjusted means for time from entering the ED to request to admit, and from request to admit to discharge (shift replaced by arrival hour)

ETHICS APPROVAL STATEMENT

NHS Research Ethics Committee approval not applicable. R&D approval for the study was granted by the participating Trust; registration number RJ114/N328.

CLINICAL TRIAL REGISTRATION

Clinical Trial Registration: Not applicable

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COMPETING INTERESTS STATEMENT

Competing Interest: None declared

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