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Prognostic value of the Glasgow Admission Prediction Score

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Title Page

Title

Prognostic value of the Glasgow Admission Prediction Score

Authors

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Word Count

2,378

Abstract

Objectives

To assess whether the Glasgow admission prediction score (GAPS) has the ability to predict hospital length of stay, six-month hospital readmission and six-month all-cause mortality.

Setting

Sampling was conducted between February and May 2016 at two separate Emergency Departments (ED), in Sheffield and Glasgow.

Participants

Data were collected prospectively at triage for consecutive adult patients who presented to the ED within sampling times. Any patients who avoided formal triage were excluded from the study. In total 1420 patients were recruited.

Primary outcomes

GAPS was calculated following triage and did not influence patient management. Length of hospital stay, hospital readmission and mortality against GAPS was modelled using survival analysis at 6 months.

Results

Of the 1420 patients recruited, 39.6% of these patients were initially admitted to hospital. At six months, 30.6% of patients had been readmitted and 5.6% of patients had died. For those admitted at first presentation, the chance of being discharged fell by 4.3% (95% confidence interval (CI) 3.2%-5.3%) per GAPS point increase. Cox regression indicated a 9.2% (95% CI 7.3%-11.1%) increase in the chance of six-month hospital readmission per point increase in GAPS. An association between GAPS and six–month mortality was demonstrated, with a hazard increase of 9% (95% CI 6.9%-11.2%) for every point increase in GAPS.

Conclusion

GAPS is predictive of hospital admission, hospital length of stay, six-month hospital readmission and six-month all-cause mortality. While GAPS primary application may be to predict admission, and support clinical decision making. GAPS may provide valuable insight into inpatient resource allocation and bed planning.

Strengths and Limitations

- This is the first study looking at GAPS as a method of predicting length of stay, readmission and mortality.
- The original derivation of GAPS presents a potential limitation, as it was carried out at a single geographical centre.
- Although this study was conducted at two geographically different regions, both EDs were tertiary units with similar resources.
- Sampling was carried out during a single period at each centre, resulting in seasonal variation in attendances and presenting complaints not being taken into account.
- Although it does aid in its implementation, the simplicity of GAPS may limit its accuracy, when compared to computerised methods.

Introduction

Crowding gives rise to a myriad of challenges for Emergency Departments (ED) and the wider hospital, resulting in poorer clinical outcomes, lower patient satisfaction and a vastly impaired working environment (1-4). As demand on EDs and hospitals continues to increase and resources remain limited, data driven models to ensure operational efficiency will gain increasing importance for improving patient flow. (5-9)

Predicting length of stay, risk of readmission and mortality are key descriptors of ED performance and can enable prediction of resource demand. These three factors are all associated with increased costs for healthcare providers. Increasing hospital LOS and readmissions represent risks to patient safety, from adverse drug reactions to hospital acquired infections (10-14). Surfacing these three key predictors of risk at triage enables enhanced clinical decision making, as well as operational demand including higher levels of care. (9, 14-15). Likewise, it could be utilised by bed managers to highlight an admitted patients likely resource usage, in terms of bed days and aid in further resource allocation for that patient. Moreover, focussed and prompt follow up on patients identified as at a high risk of readmission or 6-month mortality, would enable a targeted data driven community response (16-20).

A number of methods and tools for predicting the aforementioned outcomes have been suggested, examples include the HOSPITAL score and LACE index. (21,22) However, many are linked to specific patient cohorts and lack the capabilities to predict all of the patient outcomes discussed previously. Most importantly, the majority are not appropriate for use in the ED, due to their lack of simplicity and requirement for historical information or information obtained past the point of the ED (10-11, 20-27).

The Glasgow admission prediction score (GAPS) (Table 1) is a triage tool, utilising information readily available at the point of triage to predict patient disposition. GAPS was derived and validated from 322,000 unselected adult attendances at the NHS Greater Glasgow and Clyde ED (28). Furthermore, GAPS has been found to be an accurate predictor of patient disposition and has been found to be superior to triage nurses' ability to predict patient outcomes at the point of triage. In addition, GAPS is currently being utilised at a number of UK sites, including Glasgow, Sheffield, Nottingham and Torbay, to aid in patient streaming in the ED (28-30).

Table 1 – The Glasgow admission prediction score

Variable		Points
Age		1 point per decade
NEWS		1 point per point on NEWS
Triage Category	3	5
	2	10
	1	20
Referred by a GP		10
Arrived by ambulance		5
Admitted <1 year ago		5

NEWS – National Early Warning Score
GP – General Practitioner

Although GAPS has been employed as a method of predicting patient disposition, it has not been tested beyond the point of admission or discharge. This paper demonstrates GAPS ability to predict inpatient length of stay along with the risk of 6-month readmission and mortality.

Methods

This was a prospective observational study aiming to determine whether GAPS can predict inpatient length of stay, 6-month hospital readmission and 6-month all-cause mortality. Sampling was carried out at two large EDs in two geographically discrete areas of the UK.

Setting and participants

Data were collected on all adult attendances to ED triage at two large teaching hospitals in the UK. They were the Sheffield Teaching Hospitals NHS foundation trust ED and the Glasgow Royal Infirmary ED, each with approximately 150,000 and 95,000 annual attendances respectively.

All patients aged 16 or below who presented to the ED were not included in the study. Any patients who avoided formal triage, by being taken directly to the resuscitation room, or to minor injuries were excluded from the study. Finally, patients who left the ED before treatment was complete were also excluded from the analysis.

Data were collected at each site for all consecutive patients who attended during 21 scheduled 8-hour sampling periods. These sampling periods were arranged so every hour of each day was represented once at either site. At the Sheffield site, data were collected

between the 8th and 17th of February 2016 and at the Glasgow site, between the 5th and 26th of May 2016.

Sample size

The power calculation was based on splitting the group into a high-GAPS and low-GAPS group based on the median GAPS score. To have an 80% probability of demonstrating a hazard ratio of at least 2 (i.e. the high-GAPS group having twice the hazard of death of the low-GAPS group), with statistical significance (at $p<0.05$) required a minimum of 1307 patients, assuming an overall 6-month mortality of 5%. (31)

The sample size needed to demonstrate a similar correlation to both readmission and length of stay would be much smaller than that for mortality because of the much higher event rates. At the sample size to which we were committed by the mortality analysis, there was a near certainty of detecting a hazard ratio of 2 for readmission and index length of stay (beta>0.9999)

Ethics

The advice of the West of Scotland Research Ethics committee was sought and it was advised that this study should be considered a service evaluation. Approval was also given by the local Caldicott Guardian in Glasgow and Sheffield.

Data collection

Sampling was designed to extract data from all time periods equally, totalling 168 hours at both sampling sites. Sampling periods were arranged in shifts with researchers collecting required data on all consecutive patients at the point of triage.

GAPS was then calculated for each patient independent of patient clinical management. Any patients admitted to hospital from the ED were followed up to hospital discharge to determine inpatient length of stay. Patients were then followed up at 6 months to collect data on hospital readmission and all-cause mortality. Any patients who died in the department, or were transferred to another hospital were considered to be admitted to hospital for the purpose of the analysis.

Patient and public involvement

This study used routinely available data, therefore no patient or public involvement was required.

Statistical analysis

All statistical analysis was carried out using R v3.2.2 (32). Cox proportional hazard regression was used to determine the difference in rates of adverse outcomes according to GAPS score as a single variable. The three outcomes tested were:

1. **Inpatient length of stay,** where discharge counted as the endpoint. Any inpatient deaths during the index presentation or inpatient lengths of stay greater than 6 months were right-censored.
2. **6-month hospital readmission**. Here, the exposure to risk of readmission started at discharge from the index presentation (whether from the ED or, if admitted, from hospital). Any patient who was subsequently admitted (not just attended ED) was deemed to have reached the endpoint. Patients who reached 6 months of follow-up from the index presentation without being readmitted were right-censored. Deaths that did not occur in hospital were also right-censored. Patients who died during the index admission were not included as they were never exposed to the risk of readmission.
3. **6-month all-cause mortality**

Kaplan Meier curves were generated to illustrate the results of the Cox PH model, with three approximately equal quantiles (high, medium and low GAPS)

Results

A total of 1487 patients attended for triage during sampling periods, with 686 patients in Sheffield and 801 in Glasgow. 63 patients left the ED before treatment was completed and were therefore excluded. Another 4 patients who were admitted were lost to follow-up and consequently removed from the sample. Table 2 displays the demographics of the patients included in the analysis.

This resulted in an overall sample of 1420 patients. Of these, 563 (39.6%) were initially admitted. At six months, 435 (30.6%) had been readmitted and 80 (5.6%) had died. Firstly, the Cox proportional hazards analysis of inpatient length of stay identified a hazard ratio of 0.955 (95% CI 0.945 – 0.965). Figure 1 displays the Kaplan Meier curve for inpatient length of stay. Next, the Cox proportional hazards analysis of 6-month hospital readmission highlighted a hazard ratio of 1.092 (95% CI 1.073 – 1.111). Figure 2 displays the Kaplan Meier curve for 6-month hospital readmission. Finally, the Cox proportional hazards analysis of 6-month mortality showed a hazard ratio of 1.090 (95% CI 1.069 – 1.112). Figure 3 displays the Kaplan Meier curve for 6-month mortality.

For example, for every point increase in GAPS there was a 4.3% (95% CI 3.2%-5.3%) reduction in the chance of being discharged from hospital at any time. It is more clinically beneficial to state that for every 15-point increase in GAPS, the chance of being discharged at any one time decreased by half. Again, for every point increase in GAPS there was a 9.2%

(95% CI 7.3% - 11.1%) increase in the risk of hospital readmission at any one time during the 6-month follow-up. This can be represented as saying that for every 8-point increase in GAPS the risk of hospital readmission doubled. Lastly, for every point increase in GAPS there was a 9.0% (95% CI 6.9% - 11.2%) increase in the risk of mortality at any one point during the 6-month follow-up. This shows that for every 8-point increase in GAPS the risk of mortality doubled.

Table 2 – Demographics of Sheffield and Glasgow patients

Variable		Sheffield	Glasgow	Total
Total patients:		637	787	**1424**
Sex:	Male	294	407	**701**
	Female	343	380	**723**
Age:	10 - 19	17	17	**34**
	20 - 29	119	148	**267**
	30 - 39	60	106	**166**
	40 - 49	85	117	**202**
	50 - 59	97	147	**244**
	60 - 69	62	84	**146**
	70 - 79	84	80	**164**
	80 - 89	76	79	**155**
	90 +	37	9	**46**
Triage category:	1	26	0	**26**
	2	198	185	**383**
	3	65	528	**593**
	4	348	72	**420**
	5	0	2	**2**
NEWS score:	0	224	223	**447**
	1	187	239	**426**
	2	84	116	**200**
	3	60	75	**135**
	4	30	53	**83**
	5 +	52	81	**133**
Arrival by ambulance:	Yes	333	344	**677**
	No	304	443	**747**
Final disposition:	Admitted	233	334	**567**
	Discharged	404	453	**857**

Readmitted:	Yes	178	257	**435**
	No	464	521	**985**
Mortality:	Yes	38	42	**80**
	No	604	736	**1340**

Discussion

The results show that GAPS can predict inpatient length of stay and 6-month hospital readmission and all-cause mortality at the point of triage in the ED.

Overall, these findings highlight the fact that GAPS can be used beyond the binary prediction of patient disposition. GAPS could be utilised to identify bed days and resource usage per patient early in their presentation to hospital via the ED. As well as being beneficial to hospital bed managers to improve flow throughout the hospital, GAPS could be utilised to improve flow in the ED itself, by aiding in resource allocation. (28-30) Furthermore, GAPS could be utilised to model hospital wide demand, by applying it to the daily take. A cumulative GAPS for a day identifies hospital wide resource requirement and bed demand. GAPS could also be utilised on a larger scale, as a measure of hospital performance improvement and performance benchmarking.

The simplicity of GAPS differentiates it from other already available scoring tools used to predict patient outcomes. GAPS does not require the use of historical data or aggregation of electronic health records to identify a score, which may be a barrier to adoption. In addition, GAPS can be calculated for both medical and surgical patients. Significantly it is not a disease-specific tool and could be applied in international health systems. (20-27)

Importantly, GAPS could be used to aid ED, inpatient and operational staff in real time decision making. It gives an early indication of a patients likely current and future resource usage to the admitting clinician. GAPS is a useful aid in prioritising patients for clear management plans. This enables cohorting of patients with low GAPS in clinical areas focussed on rapid turnover, as opposed to groups of high GAPS who would benefit from early focussed input. Those patients indicated to have a short length of stay could receive early senior input to aid in faster discharges. For high GAPS patients, it could be assist in careful discharge planning, either with prompt outpatient follow-up, or by alerting a patients GP to their risk of readmission and death. Consequently, efforts could be made to either prevent this from occurring, or to plan for the eventual outcome. However, it must be stressed that clinical judgement should take precedence over GAPS in all decision making.

Future research on this topic would involve trialling GAPS in other UK centres outside of Sheffield and Glasgow. Also, it would be centred on using GAPS in a working hospital to model both resource requirements and bed demand. In addition, the practicality of utilising GAPS in real time in an ED and how these surfaced insights impact patient flow would need to be evaluated.

Conclusion

This prospective multi-centre observational study has shown that GAPS can predict inpatient length of stay and 6-month hospital readmission and mortality at the point of triage. These are in addition to previous findings proving GAPS to be an accurate predictor of patient disposition.

These new findings have a number of implications. GAPS could be utilised by hospital staff to model resource demands. In addition, focussed input on patients who have both low and high, could reduce the burden they have on health care providers. Finally, GAPS could be an invaluable adjunct to ED, inpatient and operational staff, aiding them in real time decision making. However, clinical judgement should always outweigh GAPS in decision making.

Contributorship

DJ, AC, DL, SM, CO and EL contributed to the design of the study. EL and DJ collected and recorded the data. DJ wrote the manuscript with significant input from AC, DL, SM, CO and EL during each revision.

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Competing interests

None

Data sharing statement

There are no additional unpublished data available.

Figure legend

Figure 1 – Kaplan Meier curve for inpatient length of stay. This figure displays the Kaplan Meier curves for inpatient length of stay. The data is split into three equal quantiles of low, medium and high GAPS, shown by the three separate curves. This figure indicates an increase in GAPS is associated with a longer inpatient length of stay. The logrank test p value indicates the difference in survival between the quantiles is statistically significant.

Figure 2 – Kaplan Meier curve for 6-month readmission. This figure displays the Kaplan Meier curves for 6-month readmission. The data is split into three equal quantiles of low, medium and high GAPS, shown by the three separate curves. This figure indicates an increase in GAPS is associated with a higher chance of 6-month hospital readmission. The logrank test p value indicates the difference in survival between the quantiles is statistically significant.

Figure 3 – Kaplan Meier curve for 6-month mortality. This figure displays the Kaplan Meier curves for 6-month mortality. The data is split into three equal quantiles of low, medium and high GAPS, shown by the three separate curves. This figure indicates an increase in GAPS is associated with a higher chance of 6-month mortality. The logrank test p value indicates the difference in survival between the quantiles is statistically significant.

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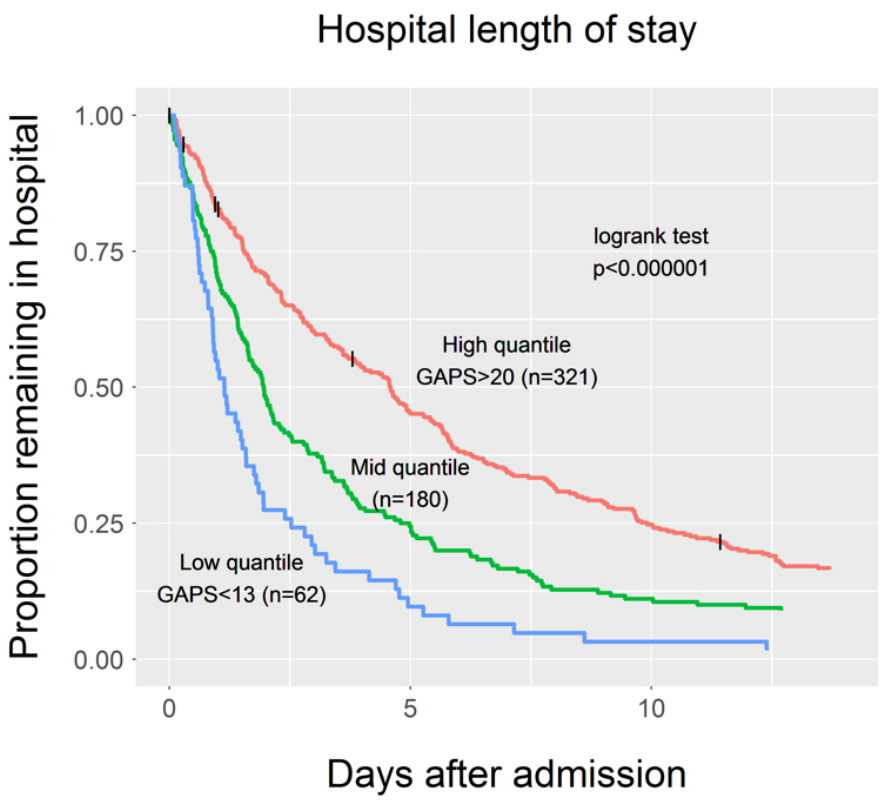

Figure 1 Kaplan Meier curve for inpatient length of stay

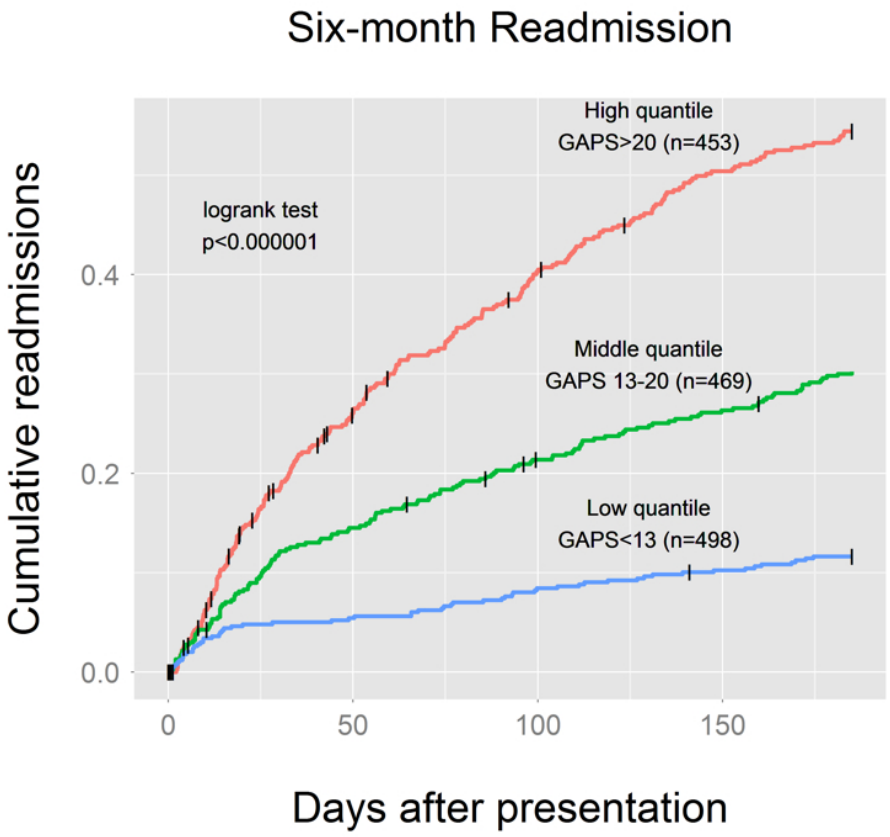

Figure 2 Kaplan Meier curve for 6-month readmission

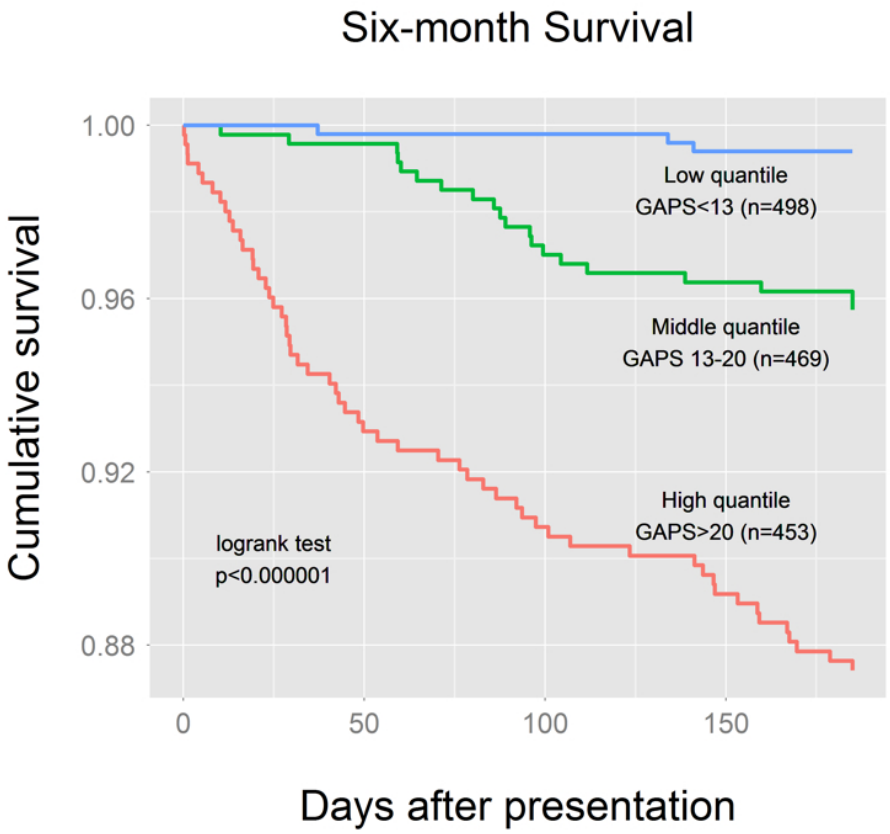

Figure 3 Kaplan Meier curve for 6-month mortality

STROBE Statement—Checklist of items that should be included in reports of ***cross-sectional studies***

	PAGE	Recommendation
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract
	2	(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found
Introduction		
Background/rationale	4	Explain the scientific background and rationale for the investigation being reported
Objectives	4	State specific objectives, including any prespecified hypotheses
Methods		
Study design	5-6	Present key elements of study design early in the paper
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection
Participants	5	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants
Variables	6-7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable
Data sources/ measurement	5-7	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group
Bias	5-6	Describe any efforts to address potential sources of bias
Study size	6	Explain how the study size was arrived at
Quantitative variables	6-7	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why
Statistical methods	6-7	(*a*) Describe all statistical methods, including those used to control for confounding
		(*b*) Describe any methods used to examine subgroups and interactions
		(*c*) Explain how missing data were addressed
		(*d*) If applicable, describe analytical methods taking account of sampling strategy
		(*e*) Describe any sensitivity analyses
Results		
Participants	7-8	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed
		(b) Give reasons for non-participation at each stage
		(c) Consider use of a flow diagram
Descriptive data	7-8	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders
		(b) Indicate number of participants with missing data for each variable of interest
Outcome data	7-8	Report numbers of outcome events or summary measures
Main results	7-8	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included
		(*b*) Report category boundaries when continuous variables were categorized
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period
Other analyses	7	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses

Discussion		
Key results	9	Summarise key results with reference to study objectives
Limitations	3	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias
Interpretation	9	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence
Generalisability	9-10	Discuss the generalisability (external validity) of the study results
Other information		
Funding	10	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based

*Give information separately for exposed and unexposed groups.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

BMJ Open

A multi-centre, prospective observational study assessing the prognostic value of the Glasgow Admission Prediction Score in predicting hospital length of stay, readmission and mortality

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Title Page

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A multi-centre, prospective observational study assessing the prognostic value of the Glasgow Admission Prediction Score in predicting hospital length of stay, readmission and mortality

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Abstract

Objectives

To assess whether the Glasgow admission prediction score (GAPS) is predictive of hospital length of stay, six-month hospital readmission and six-month all-cause mortality.

Setting

Sampling was conducted between February and May 2016 at two separate Emergency Departments (EDs), in Sheffield and Glasgow.

Participants

Data were collected prospectively at triage for consecutive adult patients who presented to the ED within sampling times. Any patients who avoided formal triage were excluded from the study. In total 1420 patients were recruited.

Primary outcomes

GAPS was calculated following triage and did not influence patient management. Length of hospital stay, hospital readmission and mortality against GAPS was modelled using survival analysis at 6 months.

Results

Of the 1420 patients recruited, 39.6% of these patients were initially admitted to hospital. At six months, 30.6% of patients had been readmitted and 5.6% of patients had died. For those admitted at first presentation, the chance of being discharged fell by 4.3% (95% confidence interval (CI) 3.2%-5.3%) per GAPS point increase. Cox regression indicated a 9.2% (95% CI 7.3%-11.1%) increase in the chance of six-month hospital readmission per point increase in GAPS. An association between GAPS and six–month mortality was demonstrated, with a hazard increase of 9% (95% CI 6.9%-11.2%) for every point increase in GAPS.

Conclusion

GAPS is predictive of hospital admission, hospital length of stay, six-month hospital readmission and six-month all-cause mortality. While GAPS' primary application may be to predict admission, and support clinical decision making. GAPS may provide valuable insight into inpatient resource allocation and bed planning.

Strengths and Limitations

- This is the first study looking at the association between GAPS and patient outcomes.
- The original derivation of GAPS presents a potential limitation, as it was carried out at a single geographical centre.
- Although this study was conducted at two geographically different regions, both EDs were tertiary units with similar resources.
- Sampling was carried out during a single period at each centre, resulting in possible seasonal idiosyncrasies affecting the results.
- Although it does aid in its implementation, the simplicity of GAPS may limit its accuracy, when compared to computerised methods.

Introduction

Crowding gives rise to a myriad of challenges for Emergency Departments (ED) and the wider hospital, resulting in poorer clinical outcomes, lower patient satisfaction and an impaired working environment (1-4). As demand on EDs and hospitals continues to increase and resources remain limited, data driven models to ensure operational efficiency will gain increasing importance for improving patient flow. (5-9)

Length of hospital stay (LOS), risk of readmission and mortality are key descriptors of hospital performance. These three factors are all associated with increased costs for healthcare providers. Increasing hospital LOS and readmissions represent risks to patient safety, from adverse drug reactions to hospital acquired infections (10-14). Predicting these outcomes at triage could enhance clinical decision making, as well as predicting operational demand, including the need for higher levels of care. (9, 14-15).

A clinician assessing a patient in the ED who knows that the patient is probabilistically at a higher risk of mortality, re-attendance, or prolonged hospital stay may be less inclined to discharge the patient without a more thorough work-up or senior advice, and conversely may be less likely to admit a low-risk patient "just in case" if their clinical parameters put them at a low risk of adverse outcomes. Moreover, focussed and prompt follow-up of patients identified as at a high risk of readmission or six-month mortality, could enable a targeted community response (16-20).

Hospital managers, who need to able to respond quickly to changes in demand for bed capacity, could have a much clearer idea of predicted bed demand if patients in the emergency department had an estimated probability of admission and predicted length of stay at an early stage in their visit.

A number of methods and tools for predicting the aforementioned outcomes have been suggested, examples include the HOSPITAL score and LACE index. (21,22) However, many are linked to specific patient cohorts and lack the capabilities to predict all of the patient outcomes discussed previously. Most importantly, the majority are not appropriate for use in the ED, due to their lack of simplicity and requirement for historical information or information obtained past the point of the ED (10-11, 20-27).

The Glasgow admission prediction score (GAPS) (Table 1) is a prediction tool, utilising information readily available to predict patient admission at the point of triage in the ED. GAPS was derived and validated from 322,000 unselected adult attendances in NHS Greater Glasgow and Clyde (28). Furthermore, GAPS has been found to be an accurate predictor of patient disposition and has been found to be superior to triage nurses' ability to predict

admission at the point of triage. In addition, GAPS is currently being utilised at a number of UK sites, including Glasgow, Sheffield, Nottingham and Torbay, to aid in patient streaming in the ED (28-30).

Table 1 – The Glasgow admission prediction score

Variable		Points
Age		1 point per decade
NEWS[1]		1 point per point on NEWS
Triage Category[2]	3	5
	2	10
	1	20
Referred by a GP[3]		10
Arrived by ambulance		5
Admitted <1 year ago		5

NEWS – National Early Warning Score (31) (See Appendix 1)
Triage Category – Manchester triage system triage category (32) (See Appendix 2)
GP – General Practitioner

Although GAPS has been employed as a method of predicting admission, it has not been shown to be predictive of patient outcomes, a fact that weakens the case for its widespread adoption.

This study represents a six-month follow-up of patients who were included in an external validation of the GAPS score's ability to predict admission at the point of triage. The results of this validation are described in an earlier paper (30).

Methods

This was a prospective observational study aiming to determine whether GAPS is predictive of inpatient length of stay, 6-month hospital readmission and 6-month all-cause mortality. Sampling was carried out at two large EDs in two geographically discrete areas of the UK.

Setting and participants

Data were collected on all adult attendances to ED triage at two large teaching hospitals in the UK. They were the Sheffield Teaching Hospitals NHS Foundation Trust ED and the Glasgow Royal Infirmary ED, having approximately 150,000 and 95,000 annual attendances respectively.

All patients aged 16 or below who presented to the ED were not included in the study. Any patients who avoided formal triage, by being taken directly to the resuscitation room, or to minor injuries were excluded from the study. Finally, patients who left the ED before treatment was complete were also excluded from the analysis.

Sample size

The power calculation was based on splitting the group into a high-GAPS and low-GAPS group based on the median GAPS score. To have an 80% probability of demonstrating a hazard ratio of at least 2 (i.e. the high-GAPS group having twice the hazard of death of the low-GAPS group), with statistical significance (at $p<0.05$) required a minimum of 1307 patients, assuming an overall 6-month mortality of 5%. (33). This also meant following patients out to six months. Although 30 days would be a more typical time period to assess unplanned re-attendance rates, we were able to assess re-attendance both at 30 days and at six months given the follow-up period.

The sample size needed to demonstrate a similar correlation to both readmission and length of stay would be much smaller than that for mortality because of the much higher event rates. At the sample size to which we were committed by the mortality analysis, there was a near certainty of detecting a hazard ratio of 2 for readmission and index length of stay (beta > 0.9999)

Ethics

The advice of the West of Scotland Research Ethics committee was sought and it was advised that this study should be considered a service evaluation. Approval was also given by the local Caldicott Guardian in Glasgow and Sheffield.

Data collection

Sampling was designed to extract data from all time periods equally, totalling 168 hours at each sampling site. Sampling periods were arranged in shifts with researchers collecting required data on all consecutive patients at the point of triage. Data were collected at each site for all consecutive patients who attended during 21 scheduled 8-hour sampling periods. These sampling periods were arranged so every hour of each day was represented once at each site. At the Sheffield site, data were collected between the 8th and 17th of February 2016 and at the Glasgow site, between the 5th and 26th of May 2016.

GAPS was then calculated for each patient independent of their clinical management. Any patients admitted to hospital from the ED were followed up to hospital discharge to determine inpatient length of stay. Patients were then followed up at 6 months to collect data on hospital readmission and all-cause mortality. These data were made available using electronic patient records. Any patients who died in the department, or were transferred to another hospital were considered to be admitted to hospital for the purpose of the analysis.

Patient and public involvement

This study used routinely collected clinical data, therefore no patient or public involvement was required.

Statistical analysis

All statistical analysis was carried out using R v3.2.2 (34). A univariate Cox proportional hazard regression was used to determine the difference in rates of endpoints according to GAPS score. The three outcomes tested were:

1. **Inpatient length of stay,** where discharge counted as the endpoint. Any inpatient deaths during the index presentation or inpatient lengths of stay greater than 6 months were right-censored.
2. **Hospital readmission**. Here, the exposure to risk of readmission started at discharge from the index presentation (whether from the ED or, if admitted, from hospital). Any patient who was subsequently admitted via an unscheduled re-attendance (and not including those who attended ED but were not admitted) was deemed to have reached the endpoint. Patients who reached 6 months of follow-up from the index presentation without being readmitted were right-censored. Deaths that did not occur in hospital were also right-censored. Patients who died during the index admission were not included as they were never exposed to the risk of readmission.
3. **All-cause mortality,** with all patients surviving beyond six months being right-censored.

Kaplan Meier curves were generated to illustrate the results of the Cox PH model, with three approximately equal quantiles (high, medium and low GAPS)

Results

A total of 1487 patients attended for triage during sampling periods, with 686 patients in Sheffield and 801 in Glasgow. 63 patients left the ED before treatment was completed and were therefore excluded. Another 4 patients who were admitted were lost to follow-up and consequently removed from the sample. Table 2 displays the demographics of the patients included in the analysis.

This resulted in an overall sample of 1420 patients. Of these, 563 (39.6%) were initially admitted. At six months, 435 (30.6%) had been readmitted and 80 (5.6%) had died. The median GAPS score was 16 (95% CI 15 – 17). Figure 1 is a flow chart illustrating this.

The Cox proportional hazards analysis of inpatient length of stay demonstrated a hazard ratio for reaching the endpoint of hospital discharge of 0.955 (95% CI 0.945 – 0.965). This

can be interpreted as a 4.3% (95% CI 3.2%-5.3%) reduction in the probability of being discharged from hospital at any time for every one-point increase in GAPS. It is perhaps more illustrative to say that for every 15-point increase in GAPS, the chance of being discharged at any one time decreased by half. Figure 2 displays the Kaplan Meier curve for inpatient length of stay in each of the three GAPS quantiles. The median length of stay for those admitted in the low GAPS quantile was 1.1 days (95% confidence interval 0.9 – 1.6 days), compared to 2.0 (1.6 – 2.3) days in the middle quantile and 4.6 (3.6 – 5.0) days in the highest quantile.

The Cox proportional hazards analysis of 6-month hospital readmission demonstrated a hazard ratio of 1.092 (95% CI 1.073 – 1.111). This means that for every one-point increase in GAPS there was a 9.2% (95% CI 7.3% - 11.1%) increase in the risk of hospital readmission at any one time during the 6-month follow-up. This can be represented as saying that for every 8-point increase in GAPS the hazard of hospital readmission doubled. The difference was also statistically significant at 30 days of follow-up, with a hazard ratio of 1.048 (1.032 – 1.065). Figure 3 displays the Kaplan Meier curve for 6-month hospital readmission.

Finally, the Cox proportional hazards analysis of 6-month mortality showed a hazard ratio of 1.090 (95% CI 1.069 – 1.112), so that for every one-point increase in GAPS there was a 9.0% (95% CI 6.9% - 11.2%) increase in the risk of mortality at any one point during the 6-month follow-up. Equivalently, for every 8-point increase in GAPS the risk of mortality doubled. Figure 4 displays the Kaplan Meier curve for 6-month mortality.

Table 2 – Demographics of Sheffield and Glasgow patients

Variable		Sheffield	Glasgow	Total
Total patients:		637	787	**1424**
Sex:	Male	294	407	**701**
	Female	343	380	**723**
Age:	10 - 19	17	17	**34**
	20 - 29	119	148	**267**
	30 - 39	60	106	**166**
	40 - 49	85	117	**202**
	50 - 59	97	147	**244**
	60 - 69	62	84	**146**
	70 - 79	84	80	**164**
	80 - 89	76	79	**155**
	90 +	37	9	**46**
Triage category:	1	26	0	**26**
	2	198	185	**383**
	3	65	528	**593**

	4	348	72	**420**
	5	0	2	**2**
NEWS score:	0	224	223	**447**
	1	187	239	**426**
	2	84	116	**200**
	3	60	75	**135**
	4	30	53	**83**
	5 +	52	81	**133**
Arrival by ambulance:	Yes	333	344	**677**
	No	304	443	**747**
Final disposition:	Admitted	233	334	**567**
	Discharged	404	453	**857**
Readmitted:	Yes	176	259	**435**
	No	461	524	**985**
Mortality:	Yes	36	44	**80**
	No	601	739	**1340**

Discussion

The results show that higher GAPS, as measured at the point of triage, is associated with increased inpatient length of stay, increased risk of 6-month hospital readmission and increased all-cause mortality, in addition to its established association with increased probability of immediate hospital admission.

These findings suggest that GAPS could be used to help inform clinicians and patients themselves of likely outcomes at an early stage in their hospital visit. GAPS could be utilised to improve flow in the ED, for example by directing low-risk patients to an ambulatory emergency care facility or urgent clinic, by giving junior clinicians a clearer idea of prognosis to support discharge decisions, or by directing senior clinicians to the patients to whose care they are most likely to add the most value. (28-30).

Beyond the ED, those patients likely to have a short length of stay could receive early senior input to aid in faster discharges. Higher GAPS scores could act as a flag for patients who may benefit from more thorough discharge planning, with prompt outpatient follow-up, to mitigate the risks of early readmission.

GAPS may also have a role in predicting hospital bed and other resource usage at an earlier stage. A hospital whose ED can estimate the probability that its patients will be admitted, and how long they are likely to require in hospital, has advance notice of its resource needs.

It could also be utilised on a larger scale, as a way to control for patient differences between departments when measuring hospital performance, or to control for differences through time at a single site embarking on service development or performance benchmarking.

The simplicity of GAPS differentiates it from other already available scoring tools used to predict patient outcomes. GAPS does not require the use of historical data or aggregation of electronic health records to identify a score, which may be a barrier to adoption. In addition, GAPS can be calculated for both medical and surgical patients. Significantly it is not a disease-specific tool and could be applied in international health systems. (20-27)

Future research on this topic would involve trialling GAPS in other UK centres outside of Sheffield and Glasgow. Also, further external validation internationally would be required to demonstrate widespread applicability. In addition, the practicality of utilising GAPS in real time in an ED and how these insights impact patient flow are yet to be formally evaluated.

This study has a number of limitations which must be highlighted. Firstly, the original derivation of GAPS was carried out at a single geographical centre. Although the current study was conducted at two geographically different regions in the UK, both EDs were tertiary units with similar resources. Sampling was carried out during a single time period at each centre, running the risk of confounding by seasonal variations in attendances and presenting complaints. The simplicity of GAPS may limit its accuracy when compared to complex computerised methods, although the simplicity does help widen its portability. The fact that NEWS and the Manchester triaging system is a parameter included in GAPS may limit its application outside of the UK.

Lastly, although this study shows a strong relationship between GAPS and the three outcome measures of interest, the predictive models developed have not been tested prospectively, and may vary according to the populations to which they are applied.

Conclusion

This prospective multi-centre observational study has shown that higher GAPS scores are associated with increased inpatient length of stay, increased risk of hospital readmission and increased mortality. These are in addition to previous findings showing GAPS to be an accurate predictor of patient disposition.

Contributorship

DJ, AC, DL, SM, CO and EL contributed to the design of the study. EL and DJ collected and recorded the data. DJ wrote the manuscript with significant input from AC, DL, SM, CO and EL during each revision.

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Competing interests

None

Data sharing statement

There are no additional unpublished data available.

Figure legend

Figure 1 – Flow chart showing distribution of measured outcomes. This figure is a flow chart displaying the measure outcomes of admission, discharge, readmission and mortality.

Figure 2 – Kaplan Meier curve for inpatient length of stay. This figure displays the Kaplan Meier curves for inpatient length of stay. The data is split into three equal quantiles of low, medium and high GAPS, shown by the three separate curves. This figure indicates an increase in GAPS is associated with a longer inpatient length of stay. The logrank test p value indicates the difference in survival between the quantiles is statistically significant.

Figure 3 – Kaplan Meier curve for 6-month readmission. This figure displays the Kaplan Meier curves for 6-month readmission. The data is split into three equal quantiles of low, medium and high GAPS, shown by the three separate curves. This figure indicates an increase in GAPS is associated with a higher chance of 6-month hospital readmission. The logrank test p value indicates the difference in survival between the quantiles is statistically significant.

Figure 4 – Kaplan Meier curve for 6-month mortality. This figure displays the Kaplan Meier curves for 6-month mortality. The data is split into three equal quantiles of low, medium and high GAPS, shown by the three separate curves. This figure indicates an increase in GAPS is associated with a higher chance of 6-month mortality. The logrank test p value indicates the difference in survival between the quantiles is statistically significant.

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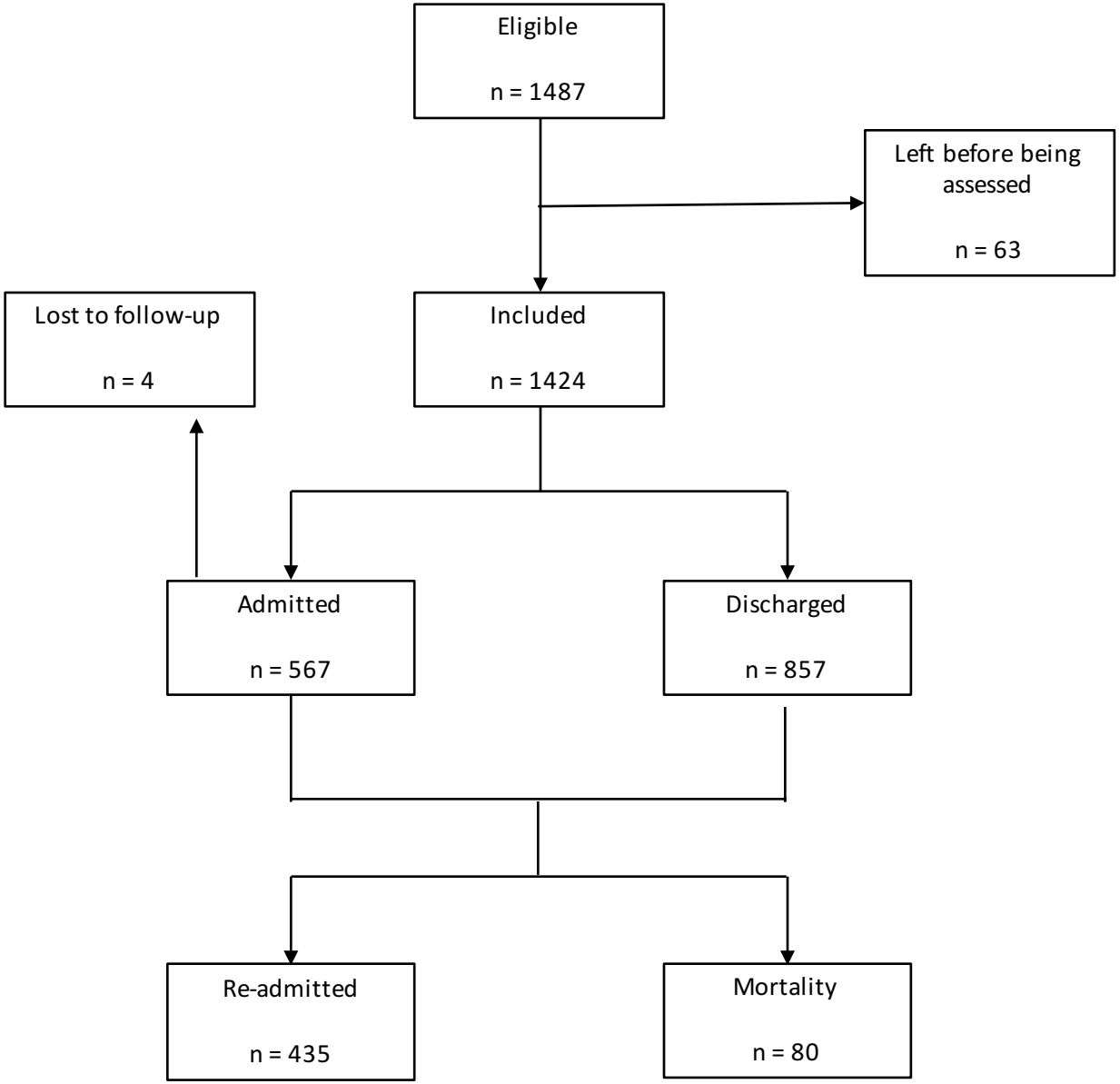
Eligible
n = 1487
Left before being assessed
n = 63
Lost to follow-up
n = 4
Included
n = 1424
Admitted
n = 567
Discharged
n = 857
Re-admitted
n = 435
Mortality
n = 80

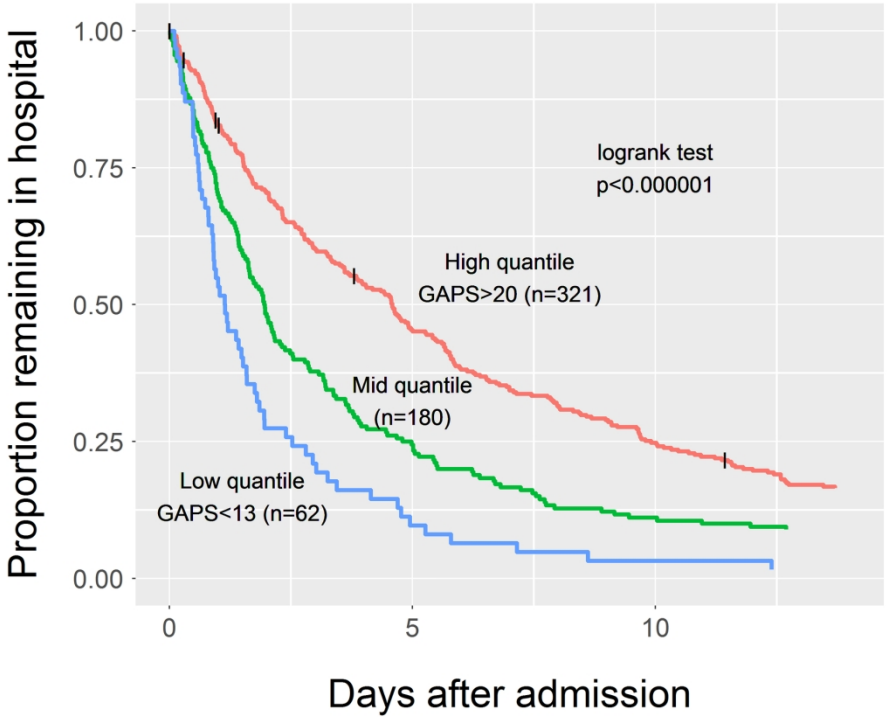

Figure 2 – Kaplan Meier curve for inpatient length of stay

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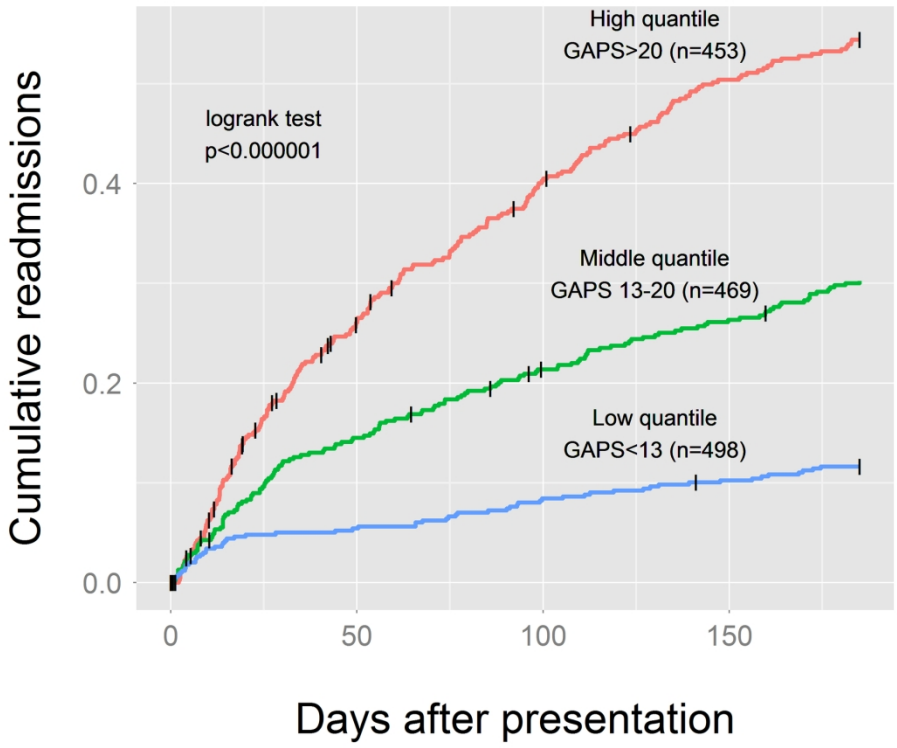

Figure 3 – Kaplan Meier curve for 6-month readmission

89x71mm (600 x 600 DPI)

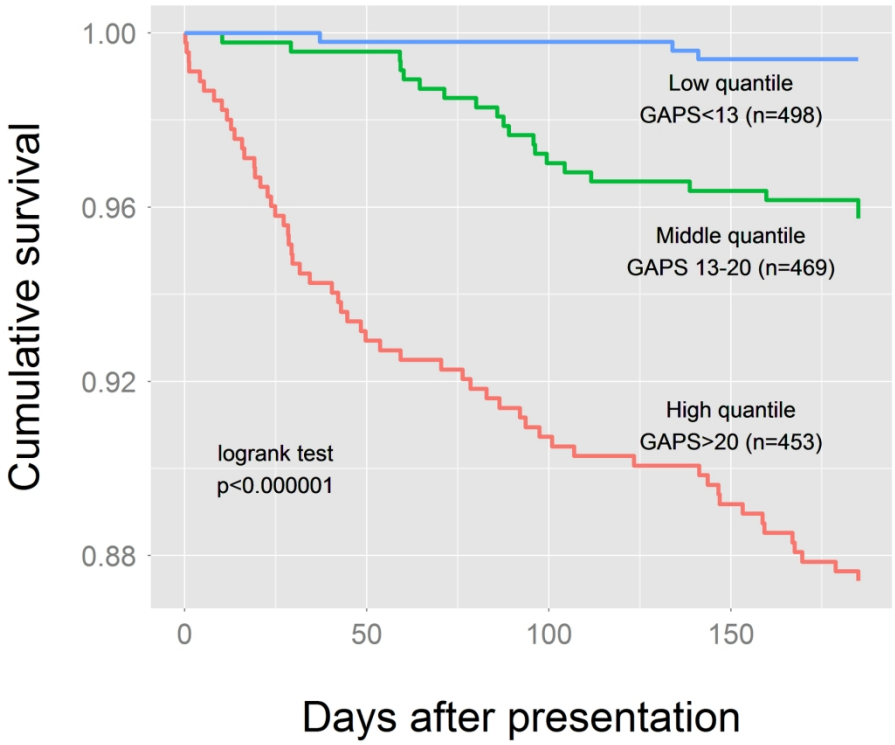

Figure 4 – Kaplan Meier curve for 6-month mortality

89x70mm (600 x 600 DPI)

Appendix 1 – The National early warning score (31)

	Score							
Variable		3	2	1	0	1	2	3
	Respiration rate	≤ 8		9 – 11	12 – 20		21-24	≥ 25
	Oxygen saturations	≤ 91	92 – 93	94 – 95	≥ 96			
	Any supplemental oxygen?		Yes		No			
	Temperature	≤ 35.0		35.1 -36.0	36.1 - 38.0	38.1 - 39.0	≥ 39.1	
	Systolic blood pressure	≤ 90	91 - 100	101 - 110	111 - 219			≥ 220
	Heart rate	≤ 40		41 - 50	51 - 90	91 - 110	111 - 130	≥ 131
	Level of consciousness (alert, voice, pain, unresponsive)				A			V, P, U

Appendix 2 – The Manchester triage system (32)

Triage Category	Name	Colour	Time to be Seen
1	Immediate	Red	0 minutes
2	Very Urgent	Orange	10 minutes
3	Urgent	Yellow	60 minutes
4	Standard	Green	120 minutes
5	Non-Urgent	Blue	240 minutes

The Manchester triage system consists of an algorithm that utilises 52 different flowchart diagrams, each of which is specific to a presenting complaint, for example chest pain or head injury. These flowcharts each have six key discriminators assigned to them, for example: time of onset, temperature, haemorrhage, pain, level of consciousness or threat to life. When a patient presents to the emergency department, the member of staff triaging the patient will assign the patient's primary complaints to the algorithm, then the final triage category will be determined using the outcomes from the algorithm and appropriate flow chart, along with fixed rules regarding the patient's vital signs measurements

STROBE Statement—Checklist of items that should be included in reports of ***cross-sectional studies***

	PAGE	Recommendation
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract
	2	(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found
Introduction		
Background/rationale	4	Explain the scientific background and rationale for the investigation being reported
Objectives	4	State specific objectives, including any prespecified hypotheses
Methods		
Study design	5-6	Present key elements of study design early in the paper
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection
Participants	5	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants
Variables	6-7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable
Data sources/ measurement	5-7	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group
Bias	5-6	Describe any efforts to address potential sources of bias
Study size	6	Explain how the study size was arrived at
Quantitative variables	6-7	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why
Statistical methods	6-7	(*a*) Describe all statistical methods, including those used to control for confounding
		(*b*) Describe any methods used to examine subgroups and interactions
		(*c*) Explain how missing data were addressed
		(*d*) If applicable, describe analytical methods taking account of sampling strategy
		(*e*) Describe any sensitivity analyses
Results		
Participants	7-8	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed
		(b) Give reasons for non-participation at each stage
		(c) Consider use of a flow diagram
Descriptive data	7-8	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders
		(b) Indicate number of participants with missing data for each variable of interest
Outcome data	7-8	Report numbers of outcome events or summary measures
Main results	7-8	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included
		(*b*) Report category boundaries when continuous variables were categorized
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period
Other analyses	7	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses

Discussion		
Key results	9	Summarise key results with reference to study objectives
Limitations	3	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias
Interpretation	9	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence
Generalisability	9-10	Discuss the generalisability (external validity) of the study results
Other information		
Funding	10	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based

*Give information separately for exposed and unexposed groups.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

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A multi-centre, prospective observational study of the correlation between the Glasgow Admission Prediction Score and adverse outcomes

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Title Page

Title

A multi-centre, prospective observational study of the correlation between the Glasgow Admission Prediction Score and adverse outcomes

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Abstract

Objectives

To assess whether the Glasgow admission prediction score (GAPS) is correlated with hospital length of stay, six-month hospital readmission and six-month all-cause mortality. This study represents a six-month follow-up of patients who were included in an external validation of the GAPS score's ability to predict admission at the point of triage

Setting

Sampling was conducted between February and May 2016 at two separate Emergency Departments (EDs), in Sheffield and Glasgow.

Participants

Data were collected prospectively at triage for consecutive adult patients who presented to the ED within sampling times. Any patients who avoided formal triage were excluded from the study. In total 1420 patients were recruited.

Primary outcomes

GAPS was calculated following triage and did not influence patient management. Length of hospital stay, hospital readmission and mortality against GAPS was modelled using survival analysis at 6 months.

Results

Of the 1420 patients recruited, 39.6% of these patients were initially admitted to hospital. At six months, 30.6% of patients had been readmitted and 5.6% of patients had died. For those admitted at first presentation, the chance of being discharged fell by 4.3% (95% confidence interval (CI) 3.2%-5.3%) per GAPS point increase. Cox regression indicated a 9.2% (95% CI 7.3%-11.1%) increase in the chance of six-month hospital readmission per point increase in GAPS. An association between GAPS and six–month mortality was demonstrated, with a hazard increase of 9% (95% CI 6.9%-11.2%) for every point increase in GAPS.

Conclusion

A higher GAPS is associated with increased hospital length of stay, six-month hospital readmission and six-month all-cause mortality. While GAPS' primary application may be to predict admission and support clinical decision making, GAPS may provide valuable insight into inpatient resource allocation and bed planning.

Strengths and Limitations

- This is the first study looking at the association between GAPS and patient outcomes.
- The original derivation of GAPS presents a potential limitation, as it was carried out at a single geographical centre.
- Although this study was conducted at two geographically different regions, both EDs were tertiary units with similar resources.
- Sampling was carried out during a single period at each centre, resulting in possible seasonal idiosyncrasies affecting the results.
- Although it does aid in its implementation, the simplicity of GAPS may limit its accuracy, when compared to computerised methods.

Introduction

Crowding gives rise to a myriad of challenges for Emergency Departments (ED) and the wider hospital, resulting in poorer clinical outcomes, lower patient satisfaction and an impaired working environment (1-4). As demand on EDs and hospitals continues to increase and resources remain limited, data driven models to ensure operational efficiency will gain increasing importance for improving patient flow. (5-9)

Length of hospital stay (LOS), risk of readmission and mortality are key descriptors of hospital performance. These three factors are all associated with increased costs for healthcare providers. Increasing hospital LOS and readmissions represent risks to patient safety, from adverse drug reactions to hospital acquired infections (10-14). Predicting these outcomes at triage could enhance clinical decision making, as well as predicting operational demand, including the need for higher levels of care. (9, 14-15).

A clinician assessing a patient in the ED who knows that the patient is probabilistically at a higher risk of mortality, re-attendance, or prolonged hospital stay may be less inclined to discharge the patient without a more thorough work-up or senior advice, and conversely may be less likely to admit a low-risk patient "just in case" if their clinical parameters put them at a low risk of adverse outcomes. Moreover, focussed and prompt follow-up of patients identified as at a high risk of readmission or six-month mortality, could enable a targeted community response (16-20).

Hospital managers, who need to able to respond quickly to changes in demand for bed capacity, could have a much clearer idea of predicted bed demand if patients in the emergency department had an estimated probability of admission and predicted length of stay at an early stage in their visit.

A number of methods and tools such as the HOSPITAL score and LACE index have been shown to be associated with the aforementioned adverse outcomes. (21,22) However, many are linked to specific patient cohorts and lack the capabilities to predict all of the patient outcomes discussed previously. Most importantly, the majority are not appropriate for use in the ED, due to their lack of simplicity and requirement for historical information or information obtained past the point of the ED (10-11, 20-27).

The Glasgow admission prediction score (GAPS) (Table 1) is a prediction tool, utilising information readily available to predict patient admission at the point of triage in the ED. GAPS was derived and validated from 322,000 unselected adult attendances in NHS Greater Glasgow and Clyde (28). Furthermore, GAPS has been found to be an accurate predictor of patient disposition and has been found to be superior to triage nurses' ability to predict admission at the point of triage. In addition, GAPS is currently being utilised at a number of

UK sites, including Glasgow, Sheffield, Nottingham and Torbay, to aid in patient streaming in the ED (28-30).

Table 1 – The Glasgow admission prediction score

Variable		Points
Age		1 point per decade
NEWS[1]		1 point per point on NEWS
Triage Category[2]	3	5
	2	10
	1	20
Referred by a GP[3]		10
Arrived by ambulance		5
Admitted <1 year ago		5

NEWS – National Early Warning Score (31) (See Appendix 1)
Triage Category – Manchester triage system triage category (32) (See Appendix 2)
GP – General Practitioner

Although GAPS has been employed as a method of predicting admission, it has not been shown to be associated with adverse patient outcomes, a fact that weakens the case for its widespread adoption. This is the first study looking at the correlation between GAPS and adverse patient outcomes.

Methods

This was a prospective observational study aiming to determine whether GAPS is correlated with inpatient length of stay, 6-month hospital readmission and 6-month all-cause mortality. Sampling was carried out at two large EDs in two geographically discrete areas of the UK. This study represents a six-month follow-up of patients who were included in an external validation of the GAPS score's ability to predict admission at the point of triage. The results of this validation are described in an earlier paper (30).

Setting and participants

Data were collected on all adult attendances to ED triage at two large teaching hospitals in the UK. They were the Sheffield Teaching Hospitals NHS Foundation Trust ED and the Glasgow Royal Infirmary ED, having approximately 150,000 and 95,000 annual attendances respectively.

All patients aged 16 or below who presented to the ED were not included in the study. Any patients who avoided formal triage, by being taken directly to the resuscitation room, or to

minor injuries were excluded from the study. Finally, patients who left the ED before treatment was complete were also excluded from the analysis.

Sample size

The power calculation was based on splitting the group into a high-GAPS and low-GAPS group based on the median GAPS score. To have an 80% probability of demonstrating a hazard ratio of at least 2 (i.e. the high-GAPS group having twice the hazard of death of the low-GAPS group), with statistical significance (at $p<0.05$) required a minimum of 1307 patients, assuming an overall 6-month mortality of 5%. (33). This also meant following patients out to six months. Although 30 days would be a more typical time period to assess unplanned re-attendance rates, we were able to assess re-attendance both at 30 days and at six months given the follow-up period.

The sample size needed to demonstrate a similar correlation to both readmission and length of stay would be much smaller than that for mortality because of the much higher event rates. At the sample size to which we were committed by the mortality analysis, there was a near certainty of detecting a hazard ratio of 2 for readmission and index length of stay (beta > 0.9999)

Ethics

The advice of the West of Scotland Research Ethics committee was sought and it was advised that this study should be considered a service evaluation. Approval was also given by the local Caldicott Guardian in Glasgow and Sheffield.

Data collection

Sampling was designed to extract data from all time periods equally, totalling 168 hours at each sampling site. Sampling periods were arranged in shifts with researchers collecting required data on all consecutive patients at the point of triage. Data were collected at each site for all consecutive patients who attended during 21 scheduled 8-hour sampling periods. These sampling periods were arranged so every hour of each day was represented once at each site. At the Sheffield site, data were collected between the 8th and 17th of February 2016 and at the Glasgow site, between the 5th and 26th of May 2016.

GAPS was then calculated for each patient independent of their clinical management. Any patients admitted to hospital from the ED were followed up to hospital discharge to determine inpatient length of stay. Patients were then followed up at 6 months to collect data on hospital readmission and all-cause mortality. These data were made available using electronic patient records. Any patients who died in the department, or were transferred to another hospital were considered to be admitted to hospital for the purpose of the analysis.

Patient and public involvement

This study used routinely collected clinical data, therefore no patient or public involvement was required.

Statistical analysis

All statistical analysis was carried out using R v3.2.2 (34). A univariate Cox proportional hazard regression was used to determine the difference in rates of endpoints according to GAPS score. The three outcomes tested were:

1. **Inpatient length of stay,** where discharge counted as the endpoint. Any inpatient deaths during the index presentation or inpatient lengths of stay greater than 6 months were right-censored.
2. **Hospital readmission**. Here, the exposure to risk of readmission started at discharge from the index presentation (whether from the ED or, if admitted, from hospital). Any patient who was subsequently admitted via an unscheduled re-attendance (and not including those who attended ED but were not admitted) was deemed to have reached the endpoint. Patients who reached 6 months of follow-up from the index presentation without being readmitted were right-censored. Deaths that did not occur in hospital were also right-censored. Patients who died during the index admission were not included as they were never exposed to the risk of readmission.
3. **All-cause mortality,** with all patients surviving beyond six months being right-censored.

Kaplan Meier curves were generated to illustrate the results of the Cox PH model, with three approximately equal quantiles (high, medium and low GAPS)

Results

A total of 1487 patients attended for triage during sampling periods, with 686 patients in Sheffield and 801 in Glasgow. 63 patients left the ED before treatment was completed and were therefore excluded. Another 4 patients who were admitted were lost to follow-up and consequently removed from the sample. Table 2 displays the demographics of the patients included in the analysis.

This resulted in an overall sample of 1420 patients. Of these, 563 (39.6%) were initially admitted. At six months, 435 (30.6%) had been readmitted and 80 (5.6%) had died. The median GAPS score was 16 (95% CI 15 – 17). Figure 1 is a flow chart illustrating this.

The Cox proportional hazards analysis of inpatient length of stay demonstrated a hazard ratio for reaching the endpoint of hospital discharge of 0.955 (95% CI 0.945 – 0.965). This can be interpreted as a 4.3% (95% CI 3.2%-5.3%) reduction in the probability of being discharged

from hospital at any time for every one-point increase in GAPS. It is perhaps more illustrative to say that for every 15-point increase in GAPS, the chance of being discharged at any one time decreased by half. Figure 2 displays the Kaplan Meier curve for inpatient length of stay in each of the three GAPS quantiles. The median length of stay for those admitted in the low GAPS quantile was 1.1 days (95% confidence interval 0.9 – 1.6 days), compared to 2.0 (1.6 – 2.3) days in the middle quantile and 4.6 (3.6 – 5.0) days in the highest quantile.

The Cox proportional hazards analysis of 6-month hospital readmission demonstrated a hazard ratio of 1.092 (95% CI 1.073 – 1.111). This means that for every one-point increase in GAPS there was a 9.2% (95% CI 7.3% - 11.1%) increase in the risk of hospital readmission at any one time during the 6-month follow-up. This can be represented as saying that for every 8-point increase in GAPS the hazard of hospital readmission doubled. The difference was also statistically significant at 30 days of follow-up, with a hazard ratio of 1.048 (1.032 – 1.065). Figure 3 displays the Kaplan Meier curve for 6-month hospital readmission.

Finally, the Cox proportional hazards analysis of 6-month mortality showed a hazard ratio of 1.090 (95% CI 1.069 – 1.112), so that for every one-point increase in GAPS there was a 9.0% (95% CI 6.9% - 11.2%) increase in the risk of mortality at any one point during the 6-month follow-up. Equivalently, for every 8-point increase in GAPS the risk of mortality doubled. Figure 4 displays the Kaplan Meier curve for 6-month mortality.

Table 2 – Demographics of Sheffield and Glasgow patients

Variable		Sheffield	Glasgow	Total
Total patients:		637	787	**1424**
Sex:	Male	294	407	**701**
	Female	343	380	**723**
Age:	10 - 19	17	17	**34**
	20 - 29	119	148	**267**
	30 - 39	60	106	**166**
	40 - 49	85	117	**202**
	50 - 59	97	147	**244**
	60 - 69	62	84	**146**
	70 - 79	84	80	**164**
	80 - 89	76	79	**155**
	90 +	37	9	**46**
Triage category:	1	26	0	**26**
	2	198	185	**383**
	3	65	528	**593**
	4	348	72	**420**
	5	0	2	**2**

NEWS score:	0	224	223	**447**
	1	187	239	**426**
	2	84	116	**200**
	3	60	75	**135**
	4	30	53	**83**
	5 +	52	81	**133**
Arrival by ambulance:	Yes	333	344	**677**
	No	304	443	**747**
Final disposition:	Admitted	233	334	**567**
	Discharged	404	453	**857**
Readmitted:	Yes	176	259	**435**
	No	461	524	**985**
Mortality:	Yes	36	44	**80**
	No	601	739	**1340**

Discussion

The results show that higher GAPS, as measured at the point of triage, is associated with increased inpatient length of stay, increased risk of 6-month hospital readmission and increased all-cause mortality, in addition to its established association with increased probability of immediate hospital admission.

These findings suggest that GAPS could be used to help inform clinicians and patients themselves of likely outcomes at an early stage in their hospital visit. GAPS could be utilised to improve flow in the ED, for example by directing low-risk patients to an ambulatory emergency care facility or urgent clinic, by giving junior clinicians a clearer idea of prognosis to support discharge decisions, or by directing senior clinicians to the patients to whose care they are most likely to add the most value. (28-30).

Beyond the ED, those patients likely to have a short length of stay could receive early senior input to aid in faster discharges. Higher GAPS scores could act as a flag for patients who may benefit from more thorough discharge planning, with prompt outpatient follow-up, to mitigate the risks of early readmission.

GAPS may also have a role in indicating hospital bed and other resource usage at an earlier stage. A hospital whose ED can estimate the probability that its patients will be admitted, and how long they are likely to require in hospital, has advance notice of its resource needs.

It could also be utilised on a larger scale, as a way to control for patient differences between departments when measuring hospital performance, or to control for differences through time at a single site embarking on service development or performance benchmarking.

The simplicity of GAPS differentiates it from other already available scoring tools associated with patient outcomes. GAPS does not require the use of historical data or aggregation of electronic health records to identify a score, which may be a barrier to adoption. In addition, GAPS can be calculated for both medical and surgical patients. Significantly it is not a disease-specific tool and could be applied in international health systems. (20-27)

Future research on this topic would involve trialling GAPS in other UK centres outside of Sheffield and Glasgow. Also, further external validation internationally would be required to demonstrate widespread applicability. In addition, the practicality of utilising GAPS in real time in an ED and how these insights impact patient flow is yet to be formally evaluated.

This study has a number of limitations which must be highlighted. Firstly, the original derivation of GAPS was carried out at a single geographical centre. Although the current study was conducted at two geographically different regions in the UK, both EDs were tertiary units with similar resources. Sampling was carried out during a single time period at each centre, running the risk of confounding by seasonal variations in attendances and presenting complaints. The simplicity of GAPS may limit its accuracy when compared to complex computerised methods, although the simplicity does help widen its portability. The fact that NEWS and the Manchester triaging system is a parameter included in GAPS may limit its application outside of the UK.

Lastly, although this study shows a strong relationship between GAPS and the three outcome measures of interest, the predictive models developed have not been tested prospectively, and may vary according to the populations to which they are applied.

Conclusion

This prospective multi-centre observational study has shown that higher GAPS scores are associated with increased inpatient length of stay, increased risk of hospital readmission and increased mortality. These are in addition to previous findings showing GAPS to be an accurate predictor of patient disposition.

Contributorship

DJ, AC, DL, SM, CO and EL contributed to the design of the study. EL and DJ collected and recorded the data. DJ wrote the manuscript with significant input from AC, DL, SM, CO and EL during each revision.

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Competing interests

None

Data sharing statement

There are no additional unpublished data available.

Figure legend

Figure 1 – Flow chart showing distribution of measured outcomes. This figure is a flow chart displaying the measure outcomes of admission, discharge, readmission and mortality.

Figure 2 – Kaplan Meier curve for inpatient length of stay. This figure displays the Kaplan Meier curves for inpatient length of stay. The data is split into three equal quantiles of low, medium and high GAPS, shown by the three separate curves. This figure indicates an increase in GAPS is associated with a longer inpatient length of stay. The logrank test p value indicates the difference in survival between the quantiles is statistically significant.

Figure 3 – Kaplan Meier curve for 6-month readmission. This figure displays the Kaplan Meier curves for 6-month readmission. The data is split into three equal quantiles of low, medium and high GAPS, shown by the three separate curves. This figure indicates an increase in GAPS is associated with a higher chance of 6-month hospital readmission. The logrank test p value indicates the difference in survival between the quantiles is statistically significant.

Figure 4 – Kaplan Meier curve for 6-month mortality. This figure displays the Kaplan Meier curves for 6-month mortality. The data is split into three equal quantiles of low, medium and high GAPS, shown by the three separate curves. This figure indicates an increase in GAPS is associated with a higher chance of 6-month mortality. The logrank test p value indicates the difference in survival between the quantiles is statistically significant.

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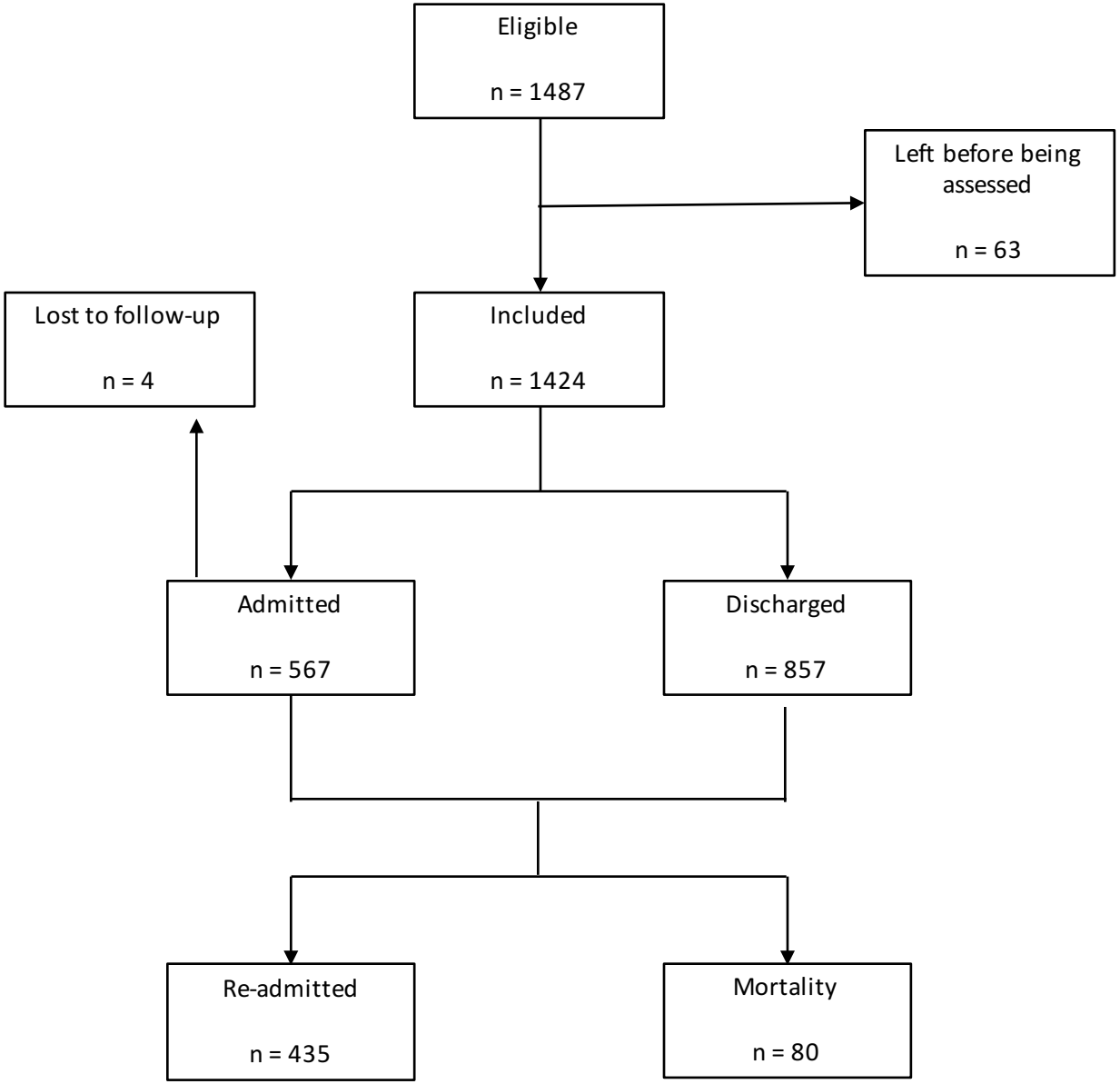
Eligible
n = 1487
Left before being assessed
n = 63
Lost to follow-up
n = 4
Included
n = 1424
Admitted
n = 567
Discharged
n = 857
Re-admitted
n = 435
Mortality
n = 80

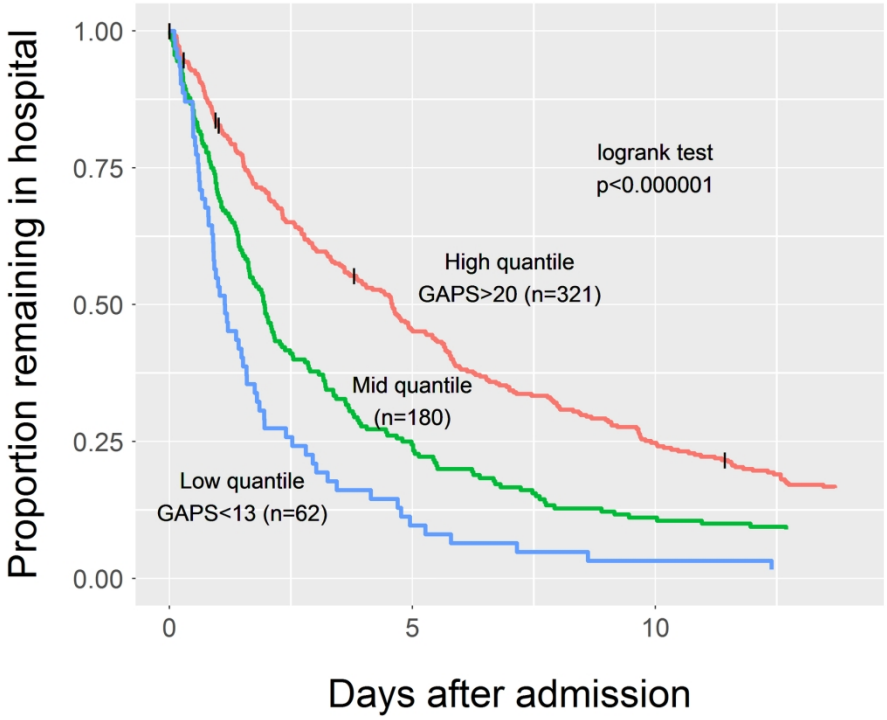

Figure 2 – Kaplan Meier curve for inpatient length of stay

89x69mm (600 x 600 DPI)

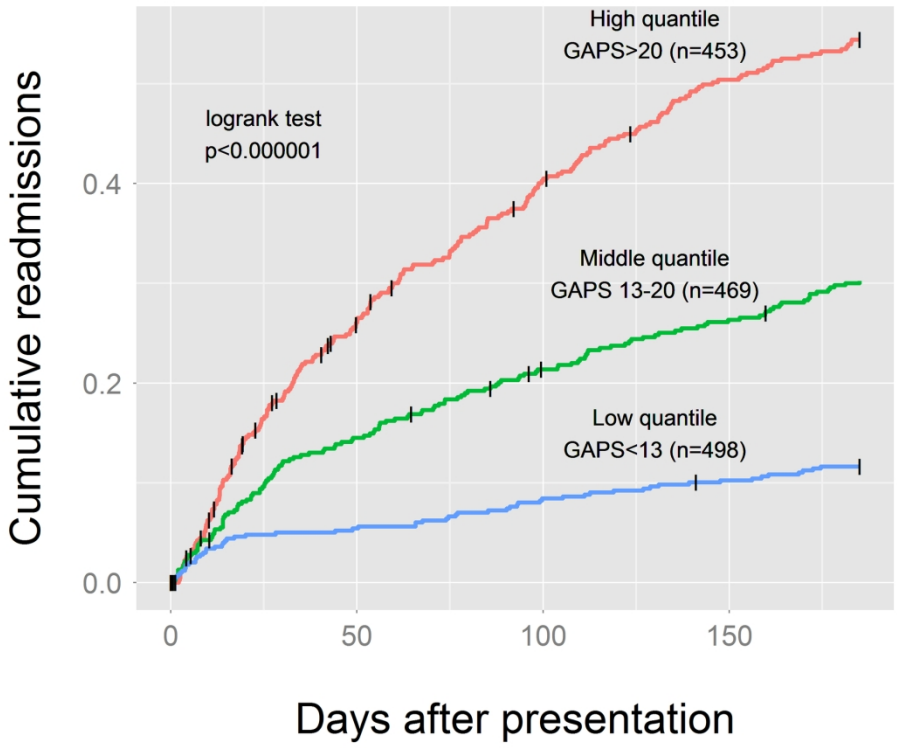

Figure 3 – Kaplan Meier curve for 6-month readmission

89x71mm (600 x 600 DPI)

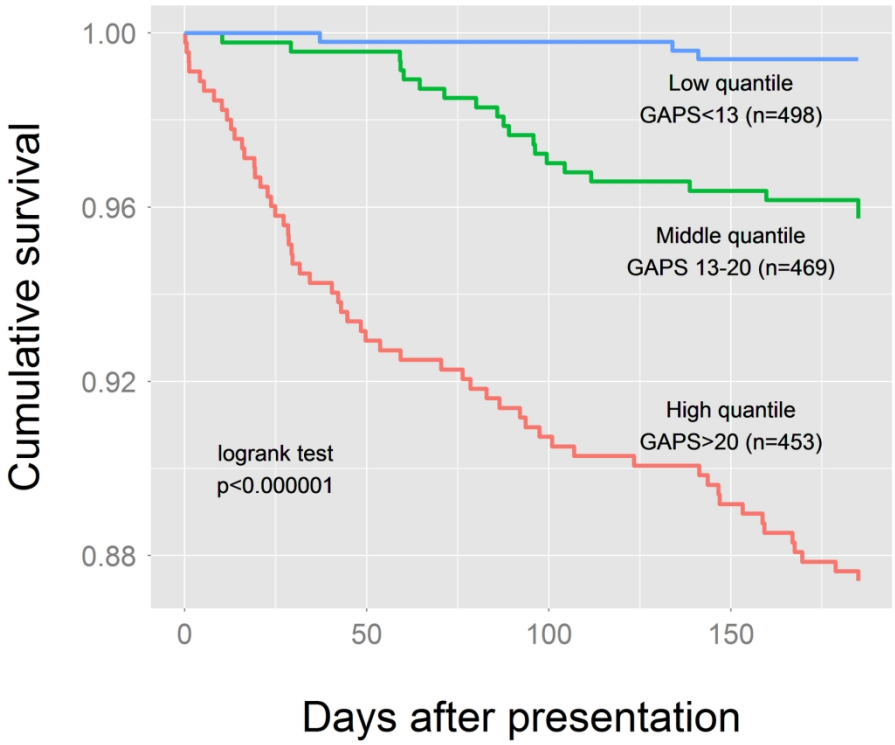

Figure 4 – Kaplan Meier curve for 6-month mortality

89x70mm (600 x 600 DPI)

Appendix 1 – The National early warning score (31)

	Score							
Variable		3	2	1	0	1	2	3
	Respiration rate	≤ 8		9 – 11	12 – 20		21-24	≥ 25
	Oxygen saturations	≤ 91	92 – 93	94 – 95	≥ 96			
	Any supplemental oxygen?		Yes		No			
	Temperature	≤ 35.0		35.1 -36.0	36.1 - 38.0	38.1 - 39.0	≥ 39.1	
	Systolic blood pressure	≤ 90	91 - 100	101 - 110	111 - 219			≥ 220
	Heart rate	≤ 40		41 - 50	51 - 90	91 - 110	111 - 130	≥ 131
	Level of consciousness (alert, voice, pain, unresponsive)				A			V, P, U

Appendix 2 – The Manchester triage system (32)

Triage Category	Name	Colour	Time to be Seen
1	Immediate	Red	0 minutes
2	Very Urgent	Orange	10 minutes
3	Urgent	Yellow	60 minutes
4	Standard	Green	120 minutes
5	Non-Urgent	Blue	240 minutes

The Manchester triage system consists of an algorithm that utilises 52 different flowchart diagrams, each of which is specific to a presenting complaint, for example chest pain or head injury. These flowcharts each have six key discriminators assigned to them, for example: time of onset, temperature, haemorrhage, pain, level of consciousness or threat to life. When a patient presents to the emergency department, the member of staff triaging the patient will assign the patient's primary complaints to the algorithm, then the final triage category will be determined using the outcomes from the algorithm and appropriate flow chart, along with fixed rules regarding the patient's vital signs measurements

STROBE Statement—Checklist of items that should be included in reports of ***cross-sectional studies***

	PAGE	Recommendation
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract
	2	(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found
Introduction		
Background/rationale	4	Explain the scientific background and rationale for the investigation being reported
Objectives	4	State specific objectives, including any prespecified hypotheses
Methods		
Study design	5-6	Present key elements of study design early in the paper
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection
Participants	5	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants
Variables	6-7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable
Data sources/ measurement	5-7	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group
Bias	5-6	Describe any efforts to address potential sources of bias
Study size	6	Explain how the study size was arrived at
Quantitative variables	6-7	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why
Statistical methods	6-7	(*a*) Describe all statistical methods, including those used to control for confounding
		(*b*) Describe any methods used to examine subgroups and interactions
		(*c*) Explain how missing data were addressed
		(*d*) If applicable, describe analytical methods taking account of sampling strategy
		(*e*) Describe any sensitivity analyses
Results		
Participants	7-8	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed
		(b) Give reasons for non-participation at each stage
		(c) Consider use of a flow diagram
Descriptive data	7-8	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders
		(b) Indicate number of participants with missing data for each variable of interest
Outcome data	7-8	Report numbers of outcome events or summary measures
Main results	7-8	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included
		(*b*) Report category boundaries when continuous variables were categorized
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period
Other analyses	7	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses

Discussion		
Key results	9	Summarise key results with reference to study objectives
Limitations	3	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias
Interpretation	9	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence
Generalisability	9-10	Discuss the generalisability (external validity) of the study results
Other information		
Funding	10	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based

*Give information separately for exposed and unexposed groups.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.