

Digital innovation in healthcare: Quantifying the impact of digital sepsis screening tools on patient outcomes, a multisite natural experiment.

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16 Abstract

17

18 The NHS ‘move to digital’ incorporating electronic patient record systems (EPR) facilitates the translation of paper-
19 based screening tools into digital systems, including digital sepsis alerts. We evaluated the impact of sepsis screening
20 tools on in-patient 30-day mortality across four multi-hospital NHS Trusts, each using a different algorithm for early
21 detection of sepsis.

22

23 Using quasi-experimental methods, we investigated the impact of the screening tools. Individual level EPR data for
24 718,000 patients between 2010 to 2020 was extracted to assess the impact on a target cohort and control cohort using
25 interrupted time series (ITS) analysis, based on a binomial regression model. We included one Trust which uses a
26 paper-based screening tool to compare the impact of digital and paper-based interventions, and one Trust which did
27 not introduce a sepsis screening tool, but did introduce an EPR.

28

29 All Trusts had lower odds of mortality, between 5 and 12%, after the introduction of the sepsis screening tool, before
30 adjustment for pre-existing trends or patient case-mix. After adjustment for existing trends, there was a significant
31 reduction in mortality in two of the three Trusts which introduced sepsis screening tools. We also observed age-
32 specific effects across Trusts.

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34 Our findings confirm that patients with similar profiles have a lower mortality risk, consistent with our previous work.
35 This study, conducted across multiple NHS Trusts, suggests that alerts could be tailored to specific patient groups
36 based on age-related effects. Different Trusts may require unique indicators, thresholds, actions, and treatments.
37 Including additional EPR information could further enhance personalised care.

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What is already known on this topic

A systematic review in 2019 found that the implementation of digital sepsis screening tools was linked to improved patient outcomes, including reductions in length of stay, but there was no evidence of associations with mortality or time to antibiotics.

What this study adds

This is the first evaluation of digital sepsis screening tools across multiple NHS hospitals in England. The results show that implementation of these digital screening tools is associated with a reduction in mortality associated with sepsis. The results also show that there are differential effects of these tools in different age groups.

How this study might affect research, practice or policy

We have shown that the picture is complex; adjusting for patient mix and pre-existing trends, the impact of sepsis screening tools differs for specific patient groups. Recent guidance from the UK NICE calls for tailored approaches to screening for sepsis and our findings support these calls. We propose that incorporating further information from the EPR could facilitate tailoring of these digital tools for specific patient populations.

Contributor statement

CEC, KH, GC and the DiAIS co-investigators conceived this study. AT and KH analysed the data. CEC, KH and AT developed the early drafts of the paper. JW, AJB, AK, ACG and SP gave insights on their specific Trusts. All authors, including RL and PG, reviewed and edited early drafts of the manuscript. All authors contributed to the article and approved the submitted version. CEC is the guarantor for this study.

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Data availability statement: The data that support the findings of this study are available via the authors of this study. Restrictions apply to the availability of these data, which were used under license for this study. Data are available via the authors in conjunction with NIHR Health Informatics Collaborative, BRIDgE and iCARE if full permissions are obtained.

92 **Introduction**

93 Sepsis is an international public health problem. Screening for sepsis is widely implemented across countries as an
94 essential approach to facilitate prompt treatment and improve patient outcomes in hospital settings, and protocols to
95 support early identification and standardised treatment of sepsis have been developed all over the world, but vary in
96 their approach..¹ The National Health Service (NHS) in England has introduced various incentives to improve sepsis
97 screening in UK hospitals.² Many screening tools which are used to support early identification of patients with
98 infection and at risk of developing organ failure were originally designed as diagnostics criteria.³ In England, all
99 healthcare organisations are expected to use the National Early Warning Score (version 2) (NEWS2), a generic
100 screening tool indicating deterioration and hence the possibility of sepsis. There is a clear advantage of a common
101 language being used across all organisations; Inada-Kim⁴ warns against ‘blinkered condition specific approaches’
102 particularly when patients are admitted as emergencies.

103
104 The NHS ‘move to digital’ through the incorporation of electronic patient record systems (EPR) facilitates the
105 translation of paper-based sepsis screening tools into digital systems, including digital sepsis alerts (DSAs). To
106 improve care for patients with sepsis, comply with national financial incentive programmes, and make best use of the
107 introduction of EPR, hospitals in England have introduced digital sepsis alerts. A variety of algorithms are in use, with
108 different workflows and different implementation strategies. A recent survey of NHS Trusts in England suggests that
109 EPR systems have been adopted by 89% of trusts, an increase from 77% in 2018.² It is not known whether the
110 translation of traditional paper-based screening tools into digital systems improves patient outcomes.

111
112 Digital alerts have generally been introduced across hospitals without randomisation or in a phased approach which
113 would have supported rigorous evaluation of their impact. A systematic review in 2019 found that the implementation
114 of digital sepsis screening tools were linked to improved patient outcomes, including reductions in length of stay, but
115 no evidence of associations with mortality or time to antibiotics.⁵ A London based study in 2020 examined the impact
116 of sepsis alerts introduced in a phased approach, and was evaluated using inverse probability of treatment weighting,
117 common in the analysis of natural experiments to emulate a RCT using real world healthcare data. This showed the
118 introduction of digital sepsis alerts was associated with a 23% lower risk of death within 30 days.⁶ Alkurti et al
119 (2022)⁷ found similar reductions in hospital mortality in children. It is not clear that current sepsis screening tools and
120 treatments are equally effective in all patient groups. Some evidence suggests that sepsis is an end-of-life condition
121 and rapid treatment may be more important for younger patients.⁸ Recently a large study has shown that patients from
122 deprived backgrounds are more likely to have sepsis and more likely to die from sepsis.⁹

123 In this multi-site study, we aimed to determine the impact of the introduction of sepsis screening tools on in-patient
124 30-day mortality. To determine whether any impact on patient outcomes is associated with the digital nature of some
125 sepsis screening tools we included a Trust which introduced a paper-based alert. To further understand whether
126 changes in patient outcomes associated with the introduction of digital sepsis alerts we included a fourth Trust and
127 considered the impact of the introduction of electronic health records as a sensitivity analysis. We considered whether
128 screening tools have a different impact on younger patients or people from more deprived backgrounds.

129

130 **Methods**

131 This was a retrospective study to analyse the impact of the introduction of different sepsis screening tools in three
132 NHS Trusts, with a fourth Trust acting as a control. The interventions in each Trust are shown in Table 1 and
133 summarised by Lazzarino et al (2024).¹⁰

134

TRUST	SEPSIS SCREENING TOOL		DATE OF INTRODUCTION	PERIOD OF INCLUSION
A	Paper based	Based on ‘Red Flad Sepsis’ ¹	April 2016	March 2010 to February 2020
B	Digital	Based on ‘Red Flag Sepsis’ ¹ , locally adapted. Calculated whenever clinical observations are entered into the EPR.	May 2016	February 2013 to February 2020
C	Digital	Alert packaged as part of Cerner’s EPR - the St John Sepsis Algorithm ² . Calculated whenever clinical observations are entered into the EPR.	April 2017	April 2010 to February 2020
D	None – EPR introduction is intervention of interest		March 2019	April 2016 to February 2020

135 Table 1: The interventions and key dates for four NHS Trusts included in the study.

136 ¹Red flag sepsis includes clinical observations and lactate levels. See Table 1 Supplementary materials in Kopcynska (2018) for further details.

137 ²St John’s Sepsis Algorithm is based on clinical observations and blood test results. See Honeyford (2020) for further details

138

139 **Timeline**

140 Trusts provided data from as early as 01/04/2010; we included data from the first day of the month where data for the
141 full month was available. The period of study ended on 31/01/2020 to account for the potential impact of COVID-19.
142 In order to use all available data we but to account for different timings of the introductions of sepsis screening tools,
143 we do not have identical periods of data for all Trusts.

144 The periods of study and the date of introduction sepsis tools is shown in Table 1.

145

146 **Study design and population**

147 Data for all adult (18+) inpatients admitted between 01/04/10 and 31/01/2020 were initially eligible for inclusion in
148 the study.

149 We identified two cohorts of patients using ICD-10 codes in the patients’ record:

150 Suspicion of Sepsis (SoS) Cohort: Patients we expected to be impacted by the introduction of a sepsis screening tool.

151 We used published ICD-10 codes associated with bacterial infections that can cause sepsis.⁷ This group is thought to
152 mitigate against bias introduced through changes in coding practices. See Box 1 for more details.

153 Control Cohort: a comparator group of patients whose outcomes we didn’t expect to be impacted by the introduction
154 of the sepsis screening tool. These patients had had an upper gastro-intestinal bleed.¹¹ We excluded patients who had
155 an ICD-10 code included in the SoS list.

156

Box 1 – Identifying patients with sepsis using routinely collected, structured data.

A key challenge in evaluating interventions to improve outcomes for patients with sepsis is that neither case note review nor administrative records are necessarily reliable for identifying patients with sepsis. The heterogenic nature of sepsis means diagnosing sepsis involves considerable subjectivity.¹² Studies have found that relying on ICD-10 sepsis specific codes in administrative data can lead to under-estimates of sepsis incidence,¹³ particularly

patients with less severe sepsis.¹⁴ In addition, sudden changes in coding practice can have a big impact.¹⁵ Many interventions, which often target sepsis awareness, can also lead to increases in the recording of sepsis. Digital interventions, such as the ones studied in this paper, often automate the coding of sepsis based on clinician responses, so may also increase the recording of ICD-10 sepsis codes. An additional challenge, which is less discussed, involves the definition of sepsis as an infection which leads to organ dysfunction, Rhee et al¹² have pointed out that it is not always clear whether the organ dysfunction is a result of the infection, but in addition, a strong sepsis intervention may reduce the opportunity of infection resulting in organ dysfunction, if the infection is identified and treated earlier. This may lead to a decrease in patients with sepsis, but may not improve more severe outcomes such as mortality.

These many challenges mean that when studying interventions to improve outcomes for patients with sepsis, focussing only on patients with an ICD-10 code for sepsis is likely to be biased, and the cause of that bias is multifactorial, and is likely to be influenced by the intervention.

In this study, we use an established list of infection codes to define the denominator, these codes have been shown to be more resistant to bias, and in this study, we include sensitivity analysis to determine if this is the case in the Trusts we have included in our analysis.

The list was developed by Inada-Kim et al¹⁶ and is known as the Suspicion of Sepsis code list; a list of codes which 'identifies patients with a bacterial infection serious enough to warrant admission'¹⁷ and considered to be as inclusive as possible.

157

158 **Data**

159 Electronic patient record (EPR) data were provided by NHS Trusts. Data used in this study were routinely collected,
160 processed by Trusts to comply with NHS requirements for Secondary Uses Service.¹⁷ These data are quality checked
161 by individual Trusts before being submitted to the NHS, and are compiled into Hospital Episode Statistics which have
162 been widely used for research in the UK.¹⁸ Data are stored by Trusts and were made accessible to us via secure data
163 environments, with appropriate data sharing and access government arrangements. See Box 2 for additional
164 information. No verbal or written informed consent from individual patients was required for data set generation. This
165 study was approved by the Health Regulatory Authority (288328).
166

Box 2 – Data Sharing

A key strength of this study was the collaboration between four NHS Trusts providing data in sharing, analysing and interpreting data. The NIHR-Health Informatics Collaborative facilitated data sharing agreements between the NHS Trusts. We worked with clinicians and health informatics specialists to develop a data dictionary enabling a wide range of research projects. Health Informatics managers at each NHS trust quality checked and processed the data according to the data dictionary, before subsequent transfer to either Imperial Clinical Analytics, Research and Evaluation (iCARE)¹⁹ or Biomedical Research Informatics Digital Environment (BRIDgE)²⁰ secure data environments.

167

168 **Data processing**

169 Each patient admission was treated as a separate event with a binary outcome: in-hospital mortality within 30 days of
170 admission. Patient demographic information was linked to hospital admissions through unique patient IDs, Patients
171 were excluded if their age or gender was missing or if their patient id was missing. Less than 15 hospital admissions
172 were excluded in each Trust.

173 **Statistical analysis**

174 *Main analysis*

175 Descriptive statistics were used to summarise in the patient cohorts over time and between Trusts.

176 We assessed the impact of the introduction of digital sepsis alerts, paper-sepsis-screening tools and the introduction of
177 an EHR on in-hospital mortality in the SoS cohort and separately on the control cohort using an interrupted time series
178 (ITS) study design, based on a segmented binomial regression model, including a time index and an intervention

179 variable to indicate whether the time variable is before or after the intervention as independent variables.²¹ This design
180 means trends before the intervention are included in the model, allowing us to compare the actual mortality rate after
181 the intervention with the counterfactual, i.e., the predicted mortality if there had been no intervention.²²

182

183 To reduce potential bias introduced by differences in the pre- and post- intervention cohorts, we adjusted for patient
184 case-mix; including age, ethnicity, gender, and comorbidities using the weighted Elixhauser score. We also adjusted
185 for hour of admission and seasonality.

186

187

188 *A priori* we considered whether sepsis alerts might have an impact on different patient groups; we hypothesised that
189 sepsis screening tools might have different effects on older, frailer patients and patients with a higher level of
190 comorbidities. We therefore modelled two interaction terms: age and comorbidities in separate models.

191

192 ***Sensitivity analyses***

193 *Sepsis incidence*:. To confirm our hypothesis that studying patients coded as having sepsis can be impacted by coding
194 practice, as described in Box 1, we plotted the incidence and mortality in patients with an SoS code and a sepsis code
195 over time.

196

197 *Additional adjustment for deprivation*: We modelled the impact of the introduction of a sepsis screening tool adjusted
198 for deprivation for these Trusts for the two Trusts were able to supply data on deprivation, based on the Index of
199 Multiple Deprivation(IMD) score.²³

200

201 **RESULTS**

202 In total, we examined mortality patterns in 607,980 SoS patients across three Trusts. In Trust A we included 156,387
203 patients who were admitted over 119 months, in Trust B 248,301 patients over 85 months, in Trust C 203,212 over
204 118 months and Trust D 110,110 over 46 months.

205 In all Trusts, the SoS cohort had more females than males, with a high proportion aged 65 and over, and the majority
206 exhibiting at least one comorbidity. Admission rates were lowest between 20:00 and 07:00. The admission rate was
207 similar in the winter and non-winter months. Approximately 40% of SoS patients at Trusts A, C and D are coded as
208 white British and Irish, compared to nearly 80% in Trust B. We included all patients, even those with missing
209 ethnicity; ethnicity was not known (either not stated or missing) for approximately one sixth of patients. See Table 2
210 for more details.

211 Trusts A, B and C had significantly lower mortality after the introduction of the sepsis screening tool before
212 adjustment for pre-existing trends or patient case-mix. After adjusting for pre-existing trends, there was a significant
213 reduction in mortality in Trusts A and C, as shown in Figures 1 and 2.

214

Table 2: Summary of patients admitted with the SoS before and after the introduction of a sepsis screening tool. Counts and % of all admissions in brackets.

	Trust A ⁴		Trust B ⁵		Trust C ⁵		Trust D ⁶	
	Before	After	Before	After	Before	After	Before	After
No. of patients admitted	79527	76860	66419	181882	116404	86888	43046	67064
Gender								
Male	34495 (43.4)	33709 (43.9)	31257 (47.1)	86356 (47.6)	52033 (44.7)	39002 (44.9)	19903 (46.2)	32130 (47.9)
Female	45032 (56.6)	43151 (56.1)	35162 (52.9)	95526 (52.4)	64371 (55.3)	47886 (55.1)	23143 (53.8)	34934 (52.1)
Ethnicity								
White British and Irish	34409 (43.3)	31053 (40.4)	53296 (80.2)	136944 (75.3)	51324 (44.1)	30006 (34.5)	19081 (44.3)	27490 (41)
Asian ¹	10217 (12.8)	11253 (14.6)	2313 (3.5)	6219 (3.4)	12540 (10.8)	9298 (10.7)	3615 (8.4)	6342 (9.5)
Black ²	4160 (5.2)	3554 (4.6)	880 (1.3)	2462 (1.4)	13354 (11.5)	9641 (11.1)	3401 (7.9)	6249 (9.3)
Any other Ethnicity	17108 (21.5)	16582 (21.6)	2741 (4.1)	9998 (5.5)	27813 (23.9)	21707 (25.0)	8482 (19.7)	14476 (21.6)
Not Stated	9662 (12.5)	12913 (16.8)	6920 (10.3)	24861 (13.6)	5309 (4.6)	10584 (12.2)	3791 (8.8)	11171 (16.7)
Not Known or Missing	3971 (5.0)	1505 (2.0)	269 (0.4)	1443 (0.7)	6064 (5.2)	5652 (6.5)	4676 (10.9)	1336 (2)
Age ³	49 (27, 64)	61 (37, 77)	55 (30, 70)	52 (29, 66)	55 (33, 70)	49 (27, 64)	59 (37, 76)	58 (36, 74)
Elixhauser score ³	5 (0,12)	3 (0, 8)	3 (0, 8)	4 (0, 10)	4 (0, 10)	5 (0,12)	2 (0, 8)	4 (0, 11)
Season of admission								
Winter (Dec-March)	32720 (37.7)	26767 (34.8)	24852 (37.4)	60158 (33.1)	37442 (32.2)	32720 (37.7)	13536 (31.4)	20736 (30.9)
Spring, Summer, Autumn (April to Nov)	51377 (62.3)	50093 (65.2)	41567 (62.6)	121724 (66.9)	78962 (67.8)	51377 (62.3)	29510 (68.6)	46328 (69.1)
Time of admission								
Morning (7:00-9:00)	10941 (12.6)	8182 (10.6)	9414 (14.2)	31682 (17.4)	14018 (12.0)	10941 (12.6)	8227 (19.1)	13768 (20.5)
Midday (10:00-13:00)	16905 (19.5)	13761 (17.9)	14385 (21.7)	43711 (24.0)	19099 (16.4)	16905 (19.5)	8646 (20.1)	14217 (21.2)
Afternoon (14:00-19:00)	28146 (32.4)	24997 (32.5)	23606 (35.5)	59811 (32.9)	39434 (33.9)	28146 (32.4)	12003 (27.9)	17958 (26.8)
Night (20:00-6:00)	30869 (35.6)	29920 (38.9)	19014 (28.6)	46678 (25.7)	43853 (37.7)	30869 (35.6)	14170 (32.9)	21121 (31.5)
Patients who died	4200 (4.8)	3017 (3.9)	3979 (6.0)	9429 (5.2)	5834 (5.0)	4200 (4.8)	1205 (2.8)	2251 (3.4)

¹Asian, Asian British and Mixed Asian

²Black, Black British and Mixed Black

³Median and interquartile range

⁴Paper based screening tool

⁵Digital based screening tool

⁶EPR introduced

Table 3: Interrupted time-series analysis of the impact of sepsis screening tools on mortality outcomes for SoS patients in three NHS Trusts in England.

Variable	Trust A		Trust B		Trust C		Trust D	
	OR (95% CI)	p value	OR (95% CI)	p value	OR (95% CI)	p value	OR (95% CI)	p value
Alert/EPR introduction	0.931 (0.822, 1.054)	0.261	0.961 (0.877, 1.053)	0.391	0.826 (0.749, 0.911)	0.0001	1.271 (1.006, 1.605)	0.0442
Time in days since the start of the study period (gradient)	1.000 (1.000, 1.000)	0.003	1.000 (1.000, 1.000)	0.041	1.000 (1.000, 1.000)	0.0003	1.000 (1.000, 1.000)	0.1468
Time in years since the start of the study period	1.044 (1.020, 1.068)	0.003	0.963 (0.929, 0.998)	0.041	1.025 (1.012, 1.039)	0.0003	0.999 (0.998, 1.000)	0.2106
Change in gradient ¹	1.000 (1.000, 1.000)	0.133	1.000 (1.000, 1.000)	0.968	1.000 (1.000, 1.000)	<0.0001	1.227 (1.098, 1.372)	0.0003
Season of admission (reference is Feb – Oct) Winter admission	1.174 (1.103, 1.250)	<0.0001	1.112 (1.061, 1.166)	<0.0001	1.097 (1.046, 1.151)	0.0001	1.000 (1.000, 1.000)	0.0000
Time of admission (reference is Morning)								
Afternoon	1.526 (1.318, 1.767)	<0.0001	1.735 (1.583, 1.901)	<0.0001	1.446 (1.313, 1.593)	<0.0001	2.468 (2.001, 3.044)	<0.0001
Midday	1.380 (1.178, 1.618)	0.0001	1.630 (1.479, 1.796)	<0.0001	1.324 (1.190, 1.473)	<0.0001	1.402 (1.098, 1.791)	0.0068
Night	1.562 (1.351, 1.807)	<0.0001	1.856 (1.692, 2.037)	<0.0001	1.565 (1.422, 1.722)	<0.0001	2.837 (2.310, 3.485)	<0.0001
Ethnicity (reference is White British and Irish)								
Ethnicity – Any other	0.658 (0.592, 0.732)	<0.0001	0.968 (0.832, 1.126)	0.675	1.042 (0.982, 1.106)	0.1771	0.815 (0.699, 0.952)	0.0096
Asian ²	1.203 (1.096, 1.321)	0.0001	0.707 (0.578, 0.866)	0.0008	0.949 (0.875, 1.029)	0.2071	0.960 (0.782, 1.177)	0.6920
Black ³	0.550 (0.430, 0.703)	<0.0001	0.952 (0.712, 1.273)	0.741	0.820 (0.753, 0.894)	<0.0001	1.173 (0.955, 1.441)	0.1284
Not Known or Missing	1.011 (0.883, 1.157)	0.877	2.765 (2.064, 3.704)	<0.0001	0.905 (0.802, 1.023)	0.1103	1.589 (1.299, 1.944)	<0.0001
Not Stated	0.878 (0.800, 0.964)	0.006	1.426 (1.325, 1.534)	<0.0001	1.309 (1.196, 1.433)	<0.0001	1.339 (1.109, 1.617)	0.0024
Age (in years)	1.051 (1.048, 1.053)	<0.0001	1.046 (1.044, 1.047)	<0.0001	1.040 (1.039, 1.042)	<0.0001	1.032 (1.029, 1.035)	<0.0001
Gender (male is reference)								
Female	0.878 (0.826, 0.933)	<0.0001	0.892 (0.852, 0.934)	<0.0001	0.932 (0.890, 0.975)	0.0024	0.918 (0.828, 1.017)	0.1026
Elixhauser score	1.112 (1.108, 1.116)	<0.0001	1.114 (1.111, 1.118)	<0.0001	1.111 (1.108, 1.114)	<0.0001	1.116 (1.110, 1.123)	<0.0001

Interrupted time-series data are presented as odds ratios (95% CI), except where specified. Values are given to three decimal places

¹Interaction between time in days since the start of the study period and the introduction of the alert

²Asian, Asian British and Mixed Asian

³Black, Black British and Mixed Black

203 In Trust A, crude analysis indicated that there was reduction in mortality rate following introduction of the screening
204 tool (see Figure 1). After adjusting for time and season of admission; and patient case mix, the screening tool showed
205 no impact on mortality (see Table 3 for more details). We investigated whether the alert had differential impacts on
206 specific patient groups by fitting interaction terms. This suggested that the introduction of the screening tool was
207 significantly associated with a reduction in mortality in older patients, but not younger patients (see Table S2 for
208 details). There was no evidence of a different impact on patients with more comorbidities.

209
210 In Trust B, prior to the introduction of a digital sepsis alert there was a decreasing trend in mortality in patients in the
211 SoS cohort and the association of the introduction of the alert with mortality is not significant in both crude and
212 adjusted analyses. However, the interaction between age and the introduction of the alert is significant, suggesting that
213 the alert had a significant impact on reducing mortality in older patients, but not in younger patients.

214
215 In Trust C there was an increasing trend in mortality prior to the introduction of a digital sepsis alert, and an increase
216 in odds of mortality of 2.6% (95%CI:1.2% to 4.0%). The introduction of the alert is associated with a decrease in odds
217 of mortality of 14% (21% to 5%). In addition, after the introduction of the alert the trend in mortality rate changes to a
218 decreasing mortality rate. However, there was no significant interaction between the introduction of the alert and age,
219 suggesting the alert does not have a differential impact in patients of different ages.

220 The introduction of the EPR in Trust D was apparently associated with an increased odds of mortality of 27%
221 (95%CI: 0.6% to 60%), we propose that this is likely to be to do with coding and recording changes as a result of both
222 the introduction of the EHR but also national sepsis coding guidelines in April 2017 and again April 2018, which have
223 been shown to have centre specific impacts on mortality.²⁴

224
225 While the primary objective of the statistical models is to assess the impact of digital sepsis screening alerts following
226 case-mix adjustment, the significance of various case-mix variables presents intriguing and complex pattern. The risk
227 of mortality rises with age over 18 and higher Elixhauser scores. Being female is associated with a decreased risk of
228 death. Additionally, mortality risk increases when patients are admitted during winter and not in the morning. The
229 influence and significance of ethnicity on the risk of mortality exhibit variations across trusts. For example, being
230 Asian or Asian British was associated with 20% higher odds of death in Trust A (95%CI:10% to 32%), a 29% lower
231 odds of death in Trust B (95%CI:13% to 42%) and no significant association with mortality in Trust C. In addition,
232 nighttime admissions had a higher risk of mortality, across all Trusts.

233 234 **Control cohort**

235 To determine if any change in mortality rate was specific to patients with an infection rather than patients who are
236 acutely deteriorating, we modelled mortality in patients with a gastric bleed, who didn't also have an SoS diagnosis.
237 There was no statistical evidence ($p>0.05$) that the introduction of sepsis screening tools was associated with a
238 decrease in mortality in this cohort. Both increasing age and Elixhauser score were significantly associated with
239 increased risk of mortality (see Table S3 & 4 in the supplementary materials for more details).

240 241 **Sensitivity Analyses**

242 **Sepsis incidence:** We investigated whether our hypothesis that the introduction of DSAs and financial incentives
243 associated with sepsis screening affected the number of people with a sepsis diagnosis; which would justify our
244 approach of using patients with a diagnosis from the Suspicion of Sepsis code list, rather than patients with an ICD-10
245 code specifically for sepsis. We found that the incidence of sepsis increases when a sepsis screening tool is introduced,
246 and again when the coding policy changed in England. Although the number of patients who died during these times
247 also increases the case fatality is less. See Figure S1 in the supplementary materials.

248
249

250 **Additional adjustment for deprivation:** Only two trusts provided data on deprivation. Including this in the model
251 had no effect on the overall model interpretation. Patients with no deprivation recorded had the highest odds of death.
252 For patients with a score, there was no significant association with mortality.
253

254 **DISCUSSION**

255

256 All Trusts had a lower mortality rate in patients with a serious infection, identified by the SoS code list, after the
257 introduction of a sepsis screening tool. After adjusting for patient case-mix, admission patterns and pre-existing
258 trends, the introduction of a sepsis screening tool was significantly associated with a decrease in mortality rate in one
259 Trust. In the remaining two Trusts, there was evidence that the introduction of a sepsis screening tool was associated
260 with a reduction in mortality rate in older patients.
261

262 We have previously shown that patients for whom a digital sepsis alert was active had a lower risk of mortality than
263 for those who had a similar profile.⁶ These results confirm these results, across multiple NHS Trusts this lower risk,
264 even when previous trends are considered. Previously, paper-based screening tools have been shown to be associated
265 with a reduced risk of mortality.²⁵ We found evidence that the introduction of a paper-based screening tool impacted
266 mortality in an older patient cohort only. We have not found previous research which has looked at the differential
267 impact of the sepsis screening tools on different groups of patients. The literature on the effectiveness of digital sepsis
268 screening tools shows that our findings, with different impact in different healthcare organisations, is consistent.
269 Evidence is unclear and the rationale for different impact in different settings is not well understood. Trust C's
270 algorithm includes blood test results, which may be more useful, or perhaps the alert introduced at Trust C was the
271 right alert for the patient population at the right time, and this is why a clear impact was seen. The underlying trend in
272 mortality prior to introduction may also be important.

273 Crude changes in mortality rates may show that sepsis screening tools reduce mortality, and many NHS Trusts have
274 highlighted the impact of new tools.²⁶ We have shown that the picture is more complex, and after adjusting for patient
275 mix and pre-existing trends the impact of sepsis screening tools may not be clear.
276

277 Across England, digital screening tools in NHS hospitals are based on paper-based screening tools embedded in
278 EPRs;² generally they do not exploit the extensive data held in EPRs or utilise machine learning algorithms to
279 personalise alerts. The picture with digital screening tools is complex, for example, evaluations of the Epic Sepsis
280 Model have suggested a reduced risk of mortality²⁷ but some suggest possible harm due to its poor diagnostic
281 performance.²⁸ Digital screening tools embedded in EPRs have advantages when compared to paper-based screening
282 systems, they can be linked directly to treatment plans, which has been shown to improve adherence.²⁹
283

284 A recent national study suggested that people of white ethnicity had the highest sepsis mortality risk.⁹ We found
285 different mortality risks for different ethnic groups between Trusts, suggesting that the impact of ethnicity is different
286 in different NHS Trusts. We retained 'not stated' and 'missing' as different ethnic groups, and saw different odds of
287 mortality, suggesting different Trusts may use these codes differently. The groups in use may not best describe ethnic
288 groups in different areas of England, and not be comparable internationally.³⁰ We explored deprivation in two trusts
289 and did not find poorer outcomes for patients from more deprived areas, but did find having no IMD score was
290 associated with poorer outcomes. This group may be more likely to have no permanent residence, and therefore be
291 representative of the most vulnerable patients.
292

293 As with many studies on sepsis, we are limited by the challenges of a gold-standard for sepsis diagnosis. We used the
294 diagnosis list suggested by Inada-Kim et al.⁴ We have explored this in Box 1. There was an increasing trend in SoS
295 admissions during the period of study. Possible causes for this include increasing numbers of admissions, or
296 increasing admissions of patients with infections, or less severely ill patients being included in the cohort due to
297 changes in coding. The use of an ITS approach takes into account underlying trends and helps to disentangle these

298 from the impact of interventions. Despite using this recommended method for determining causal inference³¹ we
299 cannot determine that the sepsis screening tools are solely responsible for changing behaviour which leads to
300 reductions in mortality, and other confounders such as changes in staffing, pressures in the hospital, paramedic
301 responses to suspected sepsis and treatment plans may be important factors in the changes we observed. Another
302 factor to consider is the potential overlap between patients with an SoS cohort and those who triggered an alert A
303 further, detailed patient level analysis which considers this in detail is in progress and part of ongoing work for a
304 separate publication. We carried out sensitivity analysis to determine if any changed in the mortality risk in SoS
305 patients were also seen in patients with a non-related condition, and found no evidence of an associated reduction in
306 mortality risk. In addition, we have shown that the introduction of an EPR was not associated with reduced in
307 mortality. In the future, we will look at patient level analysis

308
309
310 Screening tools and digital alerts should be designed with a strong evidence base. Different patient groups within
311 different Trusts may need different indicators, different thresholds for action and/or different actions and treatments. A
312 parallel qualitative study from our team¹⁰ highlights calls from healthcare practitioners, who advise that sepsis
313 screening tools should be more specific, patient-based, target healthcare practitioner teams, be portable and remotely
314 accessible, and integrate community, ambulance, and primary care with secondary care to accelerate ED triaging. A
315 key advantage of EPRs and embedded digital tools is that screening and treatment can be readily personalised, without
316 expecting health care professionals to look up specific guidance. Our results also support recent UK NICE guidelines
317 which highlights that current sepsis screening tools are dependent on use of individual variables informed by low
318 quality evidence.

319
320 For evidence-based screening tools, we need to have strong evaluations of interventions in health care, and work
321 collaboratively to share data and research methodology. The rich data from EPRs is a vital resource for identifying the
322 need for digital innovation; developing and validating models; and evaluating interventions. We have shown that with
323 detailed preparation and effective collaboration we can establish results which support a wider understanding of the
324 complex nature of preventing mortality from sepsis.

325

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401

402 **Figure Titles**

403 *Figure 1 Odds Ratios for impact of the introduction of a sepsis screening tool, adjusted for pre-existing trends, but not*
404 *for case-mix*

405 *Figure 2: 30-day mortality trend in the SoS cohort. Dots represent the actual mortality, dashed line represents the*
406 *counterfactual if there was no intervention, and the solid line represents the modelled mortality pre the intervention,*
407 *and post as if there was no intervention..*

408