Towards Data-Driven Hospital Antimicrobial Stewardship: Secondary use of Routine Electronic Care and Prescribing Records to Inform Antimicrobial Stewardship Programmes

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Abstract

Background

Hospital antimicrobial stewardship (AMS) programmes are multidisciplinary initiatives to optimise the use of antimicrobials. Most AMS programmes rely on time-consuming manual audits to monitor clinicians' antibiotic prescribing practice. Much of the information needed is already contained within electronic health records (EHRs) and could be used to inform AMS programmes. The objective of this study was to evaluate the feasibility of building analytics from hospital EHRs to facilitate AMS interventions.

Methods

This study used electronic prescribing, laboratory and clinical coding records of adult patients admitted to six specialties at Queen Elizabeth Hospital, Birmingham, UK between September 2017 and August 2018 (n = 61,679 admissions). Duration of prescribing, compliance with clinical guidelines, and timing of switch from intravenous to oral antibiotics in relation to clinical progression were assessed. Outputs were visualised at ward, specialty and consultant levels.

Results

A total of 59,884 antibacterial prescription records were linked into 24,653 therapy episodes. Among the 35% of admissions prescribed an antibacterial, the mean days of therapy per admission was 4.3 days and 9.9 days in elective and emergency hospitalisations respectively. Twenty-two percent (207/997) of therapy episodes for low-severity community-acquired pneumonia were initiated with the antibiotic recommended by locally-approved prescribing guidelines. Data suggested average delays in switching from intravenous to oral therapy of up to 3.6 days [95% CI: 3.4; 3.7]. Microbial cultures were performed prior to treatment initiation in just 22% of antibacterial prescriptions.

Conclusions

Hospital EHRs can be used to construct meaningful measures of antibiotic stewardship, demonstrating potential value for audit and feedback interventions.

1 Introduction

Antimicrobial stewardship (AMS) aims 'first, to ensure effective treatment of patients with infection, and second, to minimise collateral damage from antimicrobial use' [1]. Clinical guidelines [2–7] advocate regular clinical audits of prescriptions and feedback of results to prescribers by infection specialists. Determining prescribing quality, for example by assessing compliance with guidelines, is both labour-intensive and dependent on specialist expertise [8]. Point prevalence surveys of antibiotic prescribing are prohibitive in terms of professional time and methodological skill. Hospitals thus lack the capacity to undertake these approaches on a sufficient scale [8–10] and at regular intervals.

Electronic health records (EHRs) collected routinely by hospital information systems offer potential solutions to this problem. King et al. [11] and Hand et al. [12] scoped the potential role of electronic prescribing software in supporting prescribers across the full antibiotic lifecycle (prescription initiation; review; discontinuation and dispensing of discharge medications). Other studies have demonstrated the feasibility of using computerised laboratory results, including microbial cultures and sensitivities, to guide the choice of antimicrobial agent in empirical therapy [13] and increase the proportion of cases treated with effective antimicrobials [14].

EHRs thus have the potential to enable a range of functions recommended in AMS guidelines [2], particularly: audit of practice, feedback to prescribers, and infection surveillance. Despite this, the use of EHRs to drive AMS programmes remains modest. Extraction of records remains challenging [15], resulting in very limited secondary use for evidence-based medicine [16].

The aim of the present paper was to assess the feasibility of auditing antimicrobial stewardship practices using routinely-collected EHRs in order to provide relevant information to different AMS stakeholders including clinicians, hospital managers and policy-makers. Key objectives were to:

1. infer the indication of antibiotics prescribed to inpatients
2. assess the congruence of individual prescriptions with local prescribing guidelines, particularly in relation to empirical therapy
3. compute metrics of stewardship beyond consumption of antibiotics
4. compare these metrics between specialties and between consultant teams within specialties.

This feasibility study followed the three steps. First, we synthesised relevant antimicrobial stewardship terminology and concepts from clinical guidelines and infection surveillance protocols, and translated them into operational definitions applicable to EHRs. Second, we modelled and

visualised records to refine definitions that could be applied to data from one specialist hospital in Birmingham, UK. Third, we analysed EHRs and reviewed compliance of clinical practices with AMS guidelines.

2 Materials And Methods

2.1 Concepts and definitions

We identified relevant definitions and standards of care from international hospital antimicrobial stewardship and infection treatment guidelines from a list systematically compiled in 2018 [17], alongside four UK-specific reference sources [2, 18–20]. LS, PD and MJG narrowed down a list of concepts on the basis of (a) their relevance to inform a hospital AMS strategy, and (b) the availability of sufficient information to measure them within EHRs. These concepts are further characterised in detail and mapped onto relevant SNOMED-CT concept codes [21] in Additional file 1.

2.2 Electronic care records

Queen Elizabeth Hospital Birmingham (QEHB) is a specialist teaching hospital in Birmingham, UK with over 1,000 general and acute inpatient beds. DMcN extracted and pseudonymised EHRs for adult inpatients admitted at QEHB between 2008 and 2019: patient demographic information, clinical diagnosis codes (ICD-10 [22]), clinical procedure codes (OPCS-4 [23]), episodes of care (pseudonymised consultant code, consultant specialty) and ward movements, key investigation results (blood counts, vital signs, blood pressure, renal function, etc.). Antibacterial drug prescription and administration records were extracted from QEHB's locally-developed Prescribing, Information and Communication System (PICS) [24]. PICS is designed as per the common UK 'dose-based' prescribing approach [25], in which prescribers issue a request containing one or more drug names (Trade Family), dose, route and frequency.

MJG extracted all microbial culture results, including no growth results and cultures ordered by general practitioners, applied EUCAST interpretative criteria [26], and classified bacterial isolates by multi-drug resistance profile (multiple, extensive, and pan-drug resistance) according to rules set out by Magiorakos et al. [27].

Quantitative results reported in this paper are restricted to a subset of the entire data, corresponding to episodes of care in six specialties (general medicine, respiratory medicine, geriatric medicine, cardiology, general surgery, urology) for adult inpatients admitted between 1 September 2017 to 31 August 2018 (n = 61,679 admissions).

2.3 Data modelling and visualisation

PDM wrote data management programmes in Structured Query Language (SQL), R and tidyverse [28–30] and mapped drug names to SNOMED CT UK Drug Extension concepts [21]. A web app developed using R Shiny and JavaScript libraries [31–35] enabled data visualisation on an interactive 'antimicrobial timeline' gathering prescriptions, microbial cultures, sepsis red flags, and clinical diagnoses in a single view (Fig. 1). The timeline is accompanied by a range of biomarker charts (Additional file 2). These include relevant clinical parameters such as white blood cell counts, C-reactive protein concentrations. CURB-65 [36], an important risk stratification score for community-acquired pneumonia, was computed without the confusion score due to lack of reliable data.

Note

OOF: one-off, BD: twice per day; TDS: three times per day.

1. Screenshot of antimicrobial timeline visualisation

2.4 Construction of prescribing episodes

Graph theory principles were used to construct periods of uninterrupted antibiotic therapy (therapy episodes) by linking related prescription records. Rule definitions underpinning this linkage are available along with this paper (Additional file 3). This enabled identification of sequences of drug administration making up therapy episodes, particularly transition from one class of antimicrobials to another. Defined daily doses, days of therapy, and length of therapy (duration of the episode, irrespective of the number of antimicrobials administered concurrently) were calculated and aggregated by ward, specialty, consultant teams, and clinical indication as per definitions by Ibrahim et al. [37].

For each antimicrobial therapy episode, a dynamic table could be constructed with an hourly resolution capturing changes in therapy in relation to clinical parameters (Table 1) as the basis for adjudicating compliance with stewardship metrics.

1. Example structure of a therapy table

patient	time	mode	last WBC	WBC trend 72 h	peak CRP in last 72 hours	Last CRP	...	ABCD criteria met?
X	2018-07-31 18:49:51	IV	11.0	-0.05	151	100	...	Yes
X	2018-07-31 19:49:51	IV	8.2	-0.02	151	100	...	Yes
X	2018-07-31 20:49:51	oral	8.2	-0.02	151	40	...	Yes
...	...	...	...	...	...	...	...	...
Notes: IV: intravenous; WBC: white blood cell count; CRP: C-reactive protein concentration.								

For instance, we computed the time by which criteria for switching from intravenous to oral regimes were met, based on a set of ‘ABCD’ criteria listed in QEHB’s antimicrobial prescribing guidelines (Table 2). Out of these, ability to take oral medication (criterion B) could not be assessed from records, but other criteria could be measured continuously.

1. ABCD criteria: Considerations for intravenous to oral switch (see detailed criteria in Additional files 4 and 5)

Criteria	Markers
A Afebrile for at least 24 hours	<ul style="list-style-type: none"> • temperature 36–38 °C for 48 hours
B Able to take oral medication (<i>not measured</i>)	<ul style="list-style-type: none"> • functional gastrointestinal tract • no malabsorption • no interaction with other medications • enteral drug form available • patient can swallow and tolerate oral fluids via a tube
C Clinically improving	<ul style="list-style-type: none"> • no unexplained tachycardia (heart rate less than 90 beats/minute in the past 12 hours) • blood pressure stable in the past 24 hours • respiratory rate less than 20 breaths/minute in the past 24 hours • white cell count 4–12 × 10⁹/L OR a high white cell count that is falling • falling C-reactive protein
D Not suffering from certain deep-seated/high-risk infections	<ul style="list-style-type: none"> • Liver abscess • Osteomyelitis, Septic arthritis • Inadequately drained abscesses or empyema • Cavitating pneumonia • <i>Staphylococcus aureus</i> bacteraemia • Severe necrotising soft tissue infections • Severe infections during chemotherapy related neutropenia • Infected implants/prosthesis • Meningitis/encephalitis • Intracranial abscesses • Mediastinitis • Endocarditis • Exacerbation of cystic fibrosis/bronchiectasis

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2.5 Clinical indication training dataset

PICS captures drug prescription indications as free text. Such information was not made available to researchers due the data containing identifiable information and the high prevalence of missing data (in the region of 50%). In order to demonstrate our approach, drug indications were

instead classified retrospectively using training data. Between 2012 and 2017, a team of pharmacists led and trained by SG performed a standardised, electronically-recorded audit of antibacterials in the following specialties: general medicine, respiratory medicine, geriatric medicine, and general surgery. They reviewed information from PICS and paper clinical notes for a total of 4,200 prescriptions issued for 2,712 patients, classifying each of them into 21 possible indications including 'Not specified' and 'Other'. Of those records, 463 did not have a valid clinical indication, and 364 could not be linked to electronic prescription records, restricting the analysis to a total of 3,228 prescriptions corresponding to 2,901 therapy episodes. Indication categories with fewer than 50 episodes (endocarditis, bronchiectasis, diabetic foot and/or osteomyelitis, surgical prophylaxis) were reclassified as 'Other'. These records were used as training data to predict the clinical indication across all antimicrobial prescriptions, using random forest classification with a moderate-to-low balanced accuracy of 59% overall. Predictive analytics were estimated using repeated 5-fold stratified cross-validation and are reported in Additional file 6.

3 Results

3.1 Antimicrobial consumption descriptive characteristics

Between 1 September 2017 and 31 August 2018, there were 61,679 adult admissions (46,853 distinct patients) across the six specialties. Table 3 presents further admission and prescription characteristics by age group. Across all admissions, the mean length of stay was 4.2 days, and 21,757 (35%) contained at least one antibacterial prescription. A total of 59,884 antibacterial prescriptions were issued as part of 24,511 antibacterial therapy episodes, 141 of which spanned more than one admission. The mean length of antibacterial therapy episodes (LOT) was 5.8 days, equivalent to a mean 8.7 days of therapy (DOT) per admission. The mean days of therapy was significantly higher (9.9 days) in emergency admissions than in elective admissions (4.3 days, Fig. 2).

Therapy episodes could be analysed to study changes in antibacterial treatment choices and their timing relative to microbiological outcomes and clinical progression. One such change, de-escalation, is recommended when microbial culture and susceptibilities are available, or when there is limited evidence of infection. It is most easily measured in antibiotics with the broadest spectrum of activity, where only a small number of other drugs would have equivalent spectrum.

For instance, therapy episodes initiated with meropenem (n = 969) were most commonly:

1. (a) stopped (33%), after a mean duration of 3.0 days;
2. (b) continued (28%), after a mean duration of 2.0 days;
3. (c) switched to piperacillin + tazobactam (12%), after a mean duration of 1.1 days;
4. (d) switched to co-amoxiclav (9.1%), after a mean duration of 1.9 days;

Outcomes (c) and (d) can be regarded as de-escalation in this particular instance. It is comparatively more difficult to envisage general rules for identifying de-escalation in more common antibiotics, due to variation in local prescribing guidelines and practices.

1. Characteristics of admissions and antibacterial therapy by age group in six selected specialties (September 2017–August 2018)

ALL ADMISSIONS					ADMISSIONS WITH ≥ 1 PRESCRIPTION(S)							
Age group	Admissions N	Mean LOS (SD)	LOS IQR	DOT per 1,000 bed- days [95% CI]	Admissions N (% total admissions)	Mean LOS (SD)	LOS IQR	Prescriptions N	Therapy episodes N	Mean LOT (SD)	LOT IQR	Mean DOT (SD)
18– 24 years	3,937	1.9 (6.0)	0.2– 1.7	788 [787– 788]	1,020 (26)	4.6 (10.6)	0.8– 4.7	2,294	1,069	4.1 (7.5)	1.0– 4.4	5.7 (15.5)
25– 34 years	5,626	2.2 (6.8)	0.2– 1.8	789 [789– 790]	1,439 (26)	5.8 (12.0)	0.9– 5.9	3,523	1,541	5.1 (10.5)	1.0– 5.2	6.9 (16.2)
35– 44 years	6,389	2.5 (6.9)	0.2– 2.0	795 [794– 795]	1,617 (25)	6.6 (11.7)	1.0– 7.4	4,176	1,748	5.7 (9.8)	1.0– 6.4	7.8 (15.2)
45– 54 years	8,423	2.7 (7.2)	0.2– 2.3	827 [827– 827]	2,307 (27)	7.1 (12.0)	1.2– 8.2	5,965	2,523	5.8 (11.7)	1.0– 6.3	8.3 (21.1)
55– 64 years	9,977	3.6 (8.4)	0.2– 3.5	834 [833– 834]	3,281 (33)	8.5 (12.5)	1.6– 9.8	8,989	3,707	6.2 (10.9)	1.1– 7.0	9.2 (18.0)
65– 74 years	11,230	4.4 (9.5)	0.2– 4.7	740 [740– 740]	4,277 (38)	8.9 (13.2)	1.8– 10.3	11,620	4,868	5.6 (7.8)	1.3– 7.0	8.5 (15.1)
75– 84 years	9,815	6.3 (11.6)	0.4– 7.4	674 [674– 674]	4,440 (45)	10.7 (14.8)	2.1– 13.5	12,900	5,164	5.9 (7.1)	2.0– 7.4	9.4 (12.9)
85– 94 years	5,668	8.6 (13.1)	0.8– 11.0	618 [617– 618]	2,986 (53)	12.9 (15.4)	2.8– 17.0	9,196	3,558	6.2 (6.1)	2.0– 8.1	10.1 (12.2)
95 + years	614	10.2 (13.5)	1.0– 14.7	607 [606– 608]	390 (64)	13.4 (14.9)	2.6– 19.0	1,221	475	5.8 (5.3)	2.0– 7.3	9.7 (11.2)
All ages	61,679	4.2 (9.5)	0.2– 4.1	726 [726– 726]	21,757 (35)	9.1 (13.6)	1.6– 10.7	59,884	24,653	5.8 (8.8)	1.3– 7.0	8.7 (15.6)
Notes: CI: confident interval; DOT: days of therapy; IQR: interquartile range; LOS: length of stay (days); LOT: total length of therapy per admission (days); SD: standard deviation.												

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1. Mean and 95% CI of the total DOT per admission in patients receiving antimicrobials at any point during an admission (September 2017–August 2018)

3.2 Congruence with prescribing guidelines

Congruence of prescribing with local guidelines (first-line choice of therapy) was assessed for common infections. For instance, a total of 4,222 therapy episodes were initiated for community-acquired pneumonia (CAP), 4,109 (97%) of which could be linked with a CURB-65 severity score in the 48 hours before or after antibiotic initiation (assuming a mental confusion score of 0 due to as this information was not recorded electronically). Table 4 below reports antibiotics initiated as first-line therapy in 2,569 low-severity CAP episodes, that is, episodes with a CURB-65 score of 0 or 1. At the time of prescribing, QEHG guidelines recommended:

- CURB-65 score 0 or 1: amoxicillin; doxycycline (penicillin allergy)
- CURB-65 score 2: amoxicillin + clarithromycin; benzylpenicillin + clarithromycin; moxifloxacin (penicillin allergy)
- CURB-65 score 3+: co-amoxiclav + clarithromycin; moxifloxacin (penicillin allergy)

1. First-line therapy choice in CAP episodes in patients with a CURB-65 score of 0 or 1

	Therapy episodes n (% column total)	
First-line therapy	URB65 = 0	URB-65 = 1
Amoxicillin	205 (22.1)	249 (15.5)
Amoxicillin, clarithromycin	56 (6.0)	104 (6.5)
Azithromycin	4 (0.4)	6 (0.4)
Benzylpenicillin	2 (0.2)	3 (0.2)
Benzylpenicillin, clarithromycin	14 (1.5)	31 (1.9)
Benzylpenicillin, metronidazole	1 (0.1)	0 (0.0)
Ciprofloxacin	2 (0.2)	9 (0.6)
Clarithromycin	76 (8.2)	75 (4.7)
Clarithromycin, co-amoxiclav	261 (28.2)	541 (33.8)
Co-amoxiclav	104 (11.2)	211 (13.2)
Meropenem	9 (1.0)	24 (1.5)
Piperacillin + tazobactam	2 (0.2)	2 (0.1)
Ceftriaxone	10 (1.1)	2 (0.1)
Clarithromycin, moxifloxacin	2 (0.2)	4 (0.2)
Clarithromycin, piperacillin + tazobactam	4 (0.4)	9 (0.6)
Meropenem, vancomycin	7 (0.8)	10 (0.6)
Other	168 (18.1)	322 (20.1)
Total	927 (100)	1,602 (100)
<i>Note:</i> URB65: severity score based on CURB-65 [36], with mental confusion item set to zero: urea (blood urea nitrogen > 7 mmol/L) (1 point), respirations per minute > 30 (1 point), systolic blood pressure < 90 mmHg (1 point), age ≥ 65 years (1 point).		

Out of 927 patients whose CURB-65 score can confidently be assumed to be at the most 1 (factoring in the missing mental confusion score), just 207 (22%) therapy episodes were initiated with the recommended drug, while 331 (36%) received therapy recommended for higher CURB-65 scores.

The classifier precision for CAP was 80% (Additional file 5), indicating that one in five episodes classified as CAP potentially had a different indication. For instance, benzylpenicillin and metronidazole is the first-choice treatment option for aspiration pneumonia. Nevertheless, the low proportion of prescriptions that were congruent with guidelines was confirmed by manual inspection of individual cases.

Next, we examined adherence to microbial sampling guidelines recommending submission of bacterial cultures prior to initiation of empirical treatment [18]. We examined the proportion of prescriptions with a microbial sample taken in the three days leading up to antibacterial therapy initiation. Across a total of 59,696 prescriptions ordered by six selected specialties, 22% (n = 13,210) could be linked to at least one specimen sampled from blood, drains, respiratory tract, intravascular devices, central nervous system, aspirates or other tissue or bone samples. Narrowing the criterion to blood samples only, 18% (n = 10,906) of all prescriptions and 38% (1,174/3,107) of prescriptions for meropenem (mainly used to treat bloodstream infections), could be linked to such a sample. Figure 3 reports findings broken down by specialty and consultant team. Considerable variation can be observed, which could be further examined by exploring the indication for the prescription across each specialty/team.

1. Point and 95% confidence interval estimates of the proportion of prescriptions initiated with a blood culture sampled in the three days leading up to initiation of prescription and/or therapy by consultant team by specialty by drug type in six selected specialties (September 2017–August 2018)

3.3 Switch to oral therapy

Conversion from intravenous therapy to oral therapy is another commonly recommended stewardship intervention, which can facilitate discharge and reduce some adverse effects of injections [38]. Within 16,688 out of the 24,510 antibacterial therapy episodes, we identified 17,614 episodes consisting of one or more intravenous prescriptions. Overall, 6,404 (36%) of such the intravenous episodes were converted to oral therapy, with a median and mean duration of intravenous treatment of 2.4 days and 3.5 days respectively. On the contrary, 11,210 intravenous episodes (64%)

continued with injections until end of therapy, with a median duration of 1.3 days and a mean duration of 3.5 days. As shown in Fig. 4, variation in the conversion to oral therapy across clinical teams and specialties was evident and can be attributed, at least in part, to case mix. For instance, a likely explanation for cardiology's lower conversion rate (8%) is that prolonged intravenous therapy is recommended for deep-seated infections such as endocarditis.

1. Point and 95% confidence interval estimates of the proportion of intravenous therapy converted to oral therapy ranked by consultant team by specialty (September 2017–August 2018)

We sought to analyse the timeliness of conversion from intravenous to oral therapy. Despite the limited scientific evidence on oral conversion criteria, some simple clinical stability criteria have been promoted and included in clinical guidelines. We chose one such set of criteria in place in QEHB, known as ABCD (Table 2). Out of 6,404 intravenous episodes successfully switched, 2,670 (42%) met A, C and D criteria before oral conversion occurred. Out of 11,210 sequences never switched, 2,682 (21%) met A, C and D criteria before end of therapy. Across both sets, the delay between criteria being met and end/conversion of therapy had a median of 2.1 days, a mean of 3.6 days [95% CI: 3.4; 3.7], and a standard deviation of 5.7 days, suggesting considerable variation. Figure 5 presents team- and specialty-level mean delays, suggesting once again some differences between consultant teams within specialties.

1. Point and 95% confidence interval estimates of the mean time (days) elapsed between ABCD criteria being met and conversion to oral therapy, ranked by consultant team by specialty (September 2017–August 2018)

4 Discussion

4.1 Principal findings

This single-site clinical audit demonstrates a pragmatic approach to draw on electronic prescription, laboratory and hospital care records to provide meaningful measures of AMS. While this approach cannot be used to provide feedback on the appropriateness of individual-level prescribing decisions, it can identify areas of prescribing behaviour where there is scope for improved stewardship. For example, our findings in relation to compliance with guidelines for low severity CAP highlight potential to optimise empirical prescribing for this common clinical infection syndrome. Similarly, the stewardship metrics we have developed provide a means of monitoring variation in prescribing behaviours across consultant teams and specialties, providing scope to: monitor performance; inform the design of stewardship interventions; evaluate their impact; and engage clinical teams in audit and feedback interventions to optimise their prescribing. Our approach also makes it easier for clinicians to visualise and review patients' prescribing and infection history without requiring lengthy exploration of medical notes.

This feasibility study also reveals the challenges associated with assessing congruence with local prescribing guidelines and the complexity of prescribing decisions. Manual review of individual prescribing records led authors to conclude that there is too much ambiguity in electronic health records to confidently assess the appropriateness of prescribing decisions. Greater clinical research is needed in this field to develop evidence-based standards of care for antimicrobial stewardship (for instance on de-escalation [39]), which could be facilitated by observational studies of routine care records.

4.2 Study strengths and limitations

This study is novel in attempting to measure clinical constructs that normally require manual audits or point prevalence surveys [19, 40]. We outlined ways of measuring (and benchmarking) quality of stewardship in clinical practice beyond antimicrobial consumption, which is the main method currently used in antimicrobial surveillance [41]. National surveillance systems for prescribing and resistance in secondary care provide high-quality measures of resistance and prescribing for policy-makers, but they do not address the needs of front-line clinicians who require more detailed metrics to identify opportunities to improve their performance. The approach outlined in this study demonstrates the potential for locally-developed analytics to address the local needs and stewardship priorities of clinicians using routinely-collected EHRs.

Existing literature contains few examples of EHR research simultaneously analysing electronic prescribing, laboratory and care records outside of intensive care research. To our knowledge, only large bespoke data engineering platforms have achieved this [42–44]. Unlike the present study, such platforms exploit health messages streaming from hospital information systems in real-time: these contain dynamic information, unlike the retrospective view provided from EHRs commonly curated in hospital warehouses. This noteworthy difference has implications: although dynamic health messages can contain greater detail on clinical decisions, their structure and content is more variable across systems and can involve greater investment in the development of dedicated data models and analytical processing. Consequently, these are currently out of reach of most hospitals. The pragmatic approach described in the present paper, although more rudimentary, is potentially more easily adoptable to a wider range of hospitals, provided that interoperable software can be made available.

This single-site feasibility study exhibits several limitations. Gaps in access to dispensing records prevented analysis of “to take away” medications issued at discharge. Similarly, some diagnostics results (for instance chest radiology reports on lung consolidations, a criterion for the diagnosis and treatment of pneumonia) were not available and prevent detailed analysis of diagnostics stewardship. Finally, prescription records obtained

from a snapshot source did not include a history of changes made to prescriptions’ intended duration. This prevented analysis of how frequently prescriptions were stopped early. All analyses were restricted to structured data, and did not attempt to derive information which may have been recorded in free text in medical notes.

4.3 Implications

International guidelines recommend investment in surveillance and analytics to rationalise the use of antimicrobials. Electronic prescription, laboratory and hospital care record systems are rapidly becoming commonplace in high-income nations. The UK’s Antimicrobial Resistance National Action Plan [45] aims to complete the introduction of electronic prescribing systems across England by 2025, alongside the adoption of international clinical terminology in computerised laboratory systems [46]. Strong evidence supports the use of feedback to prescribers [2, 47], but feedback needs to be relevant, reliable and timely to influence prescribing behaviour [48]. Further research is needed to statistically adjust those measures for case mix in the same way as consumption measures [49]. User-centred research [50] is also needed to tailor these measures to individual clinical teams, or to enable AMS teams or hospital managers to monitor specific prescribing behaviours across hospitals.

5 Conclusions

This single-site clinical audit shows it is feasible to draw on electronic prescription, laboratory and hospital care records to provide meaningful measures of AMS, by:

1. **Reconstructing ‘therapy episodes’**, which link all relevant prescription records and enable analyses of the length, changes and discontinuation of antimicrobial therapy.
2. **Inferring the clinical intent and indication of prescriptions** (for both monotherapy and combination therapy). We have illustrated the use of supervised classification in general medicine specialties with moderate accuracy for the most common infection categories.
3. **Computing stewardship performance and quality metrics**. Examples include conversion of intravenous therapy to oral therapy when patients show signs of resolution, microbial culture sampling and congruence with guidelines.

One of the most significant obstacles hindering hospitals’ stewardship efforts lies the difficulty in extracting and analysing EHRs from a range of diverse systems [16]. Reproducible analytical tools are now available to assist microbiology culture and sensitivity analytics [51]. Software development is underway support other hospitals in adopting the approach tested in the present study.

Abbreviations

AMS	antimicrobial stewardship
CAP	community-acquired pneumonia
CRP	C-reactive protein
DOT	days of therapy
EHR	electronic health record
IV	intravenous
LOT	length of therapy
PICS	Prescribing, Information and Communication System
QEHb	Queen Elizabeth Hospital Birmingham
UK	United Kingdom
WBC	white blood cell count

Declarations

Ethics approval and consent to participate

This research was approved by University College London’s Research Ethics Committee (REC reference 16765/002). Informed consent was not sought for the secondary analysis of pseudonymised electronic health records.

Consent for publication

Not applicable.

Availability of data and materials

The pseudonymised datasets analysed during the current study are not publicly available due to residual risk of patient identifiability.

Competing interests

None to declare.

Authors' contributions

DMcN extracted data for the study team. MJG extracted and classified microbial culture and sensitivity records. GS led the collection of the prescription review data. PDM programmed and conducted analyses, and drafted the manuscript. MJG, LS, AH and PDM reviewed visualisations of results and interpreted the findings. All authors have read and approved the submitted manuscript.

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Figures

Figure 1

Screenshot of antimicrobial timeline visualisation

Figure 2

Mean and 95% CI of the total DOT per admission in patients receiving antimicrobials at any point during an admission (September 2017–August 2018)

Figure 3

Point and 95% confidence interval estimates of the proportion of prescriptions initiated with a blood culture sampled in the three days leading up to initiation of prescription and/or therapy by consultant team by specialty by drug type in six selected specialties (September 2017–August 2018)

Figure 4

Point and 95% confidence interval estimates of the proportion of intravenous therapy converted to oral therapy ranked by consultant team by specialty (September 2017–August 2018)

Figure 5

Point and 95% confidence interval estimates of the mean time (days) elapsed between ABCD criteria being met and conversion to oral therapy, ranked by consultant team by specialty (September 2017–August 2018)

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