JAC Antimicrob Resist
https://doi.org/10.1093/jacamr/dlad019

JAC-Antimicrobial Resistance

Utility of a risk assessment model in predicting 30 day unplanned hospital readmission in adult patients receiving outpatient parenteral antimicrobial therapy

Ethan Brenneman [1]*, Jason Funaro[1], Kristen Dicks[2], Michael Yarrington[2], Hui-Jie Lee[3], Alaattin Erkanli[3], Frances Hung[3] and Richard Drew[2,4]

[1]Department of Pharmacy, Duke University Hospital, 2301 Erwin Road Durham, Durham, NC, USA; [2]Division of Infectious Diseases, Duke University School of Medicine, Durham, NC, USA; [3]Biostatistics & Bioinformatics, Duke University School of Medicine, Durham, NC, USA; [4]Campbell University College of Pharmacy & Health Sciences, Buies Creek, NC, USA

*Corresponding author. E-mail: Ethan.brenneman@duke.edu
@EthanBPharmD, @JasonFunaro

Received 12 December 2022; accepted 1 February 2023

Objectives: Outpatient parenteral antimicrobial therapy (OPAT) is associated with high hospital readmission rates. A 30 day unplanned readmission risk prediction model for OPAT patients has been developed in the UK. Given significant differences in patient mix and methods of OPAT delivery, we explored the model for its utility in Duke University Health System (DUHS) patients receiving OPAT.

Methods: We analysed OPAT episodes of adult patients from two hospitals between 1 July 2019 and 1 February 2020. The discriminative ability of the model to predict 30 day unplanned all-cause and OPAT-related admission was examined. An updated model was created by logistic regression with the UK risk factors and additional risk factors, OPAT delivery in a skilled nursing facility, vancomycin use and IV drug abuse.

Results: Compared with patients of the UK cohort, our study patients were of higher acuity, treated for more invasive infections, and received OPAT through different modes. The 30 day unplanned readmission rate in our cohort was 20% (94/470), with 59.5% (56/94) of those being OPAT-related. The original model was unable to discriminate for all-cause readmission with a C-statistic of 0.52 (95% CI 0.46–0.59) and for OPAT-related readmission with a C-statistic of 0.55 (95% CI 0.47–0.64). The updated model with additional risk factors did not have improved performance, with a C-statistic of 0.55 (95% CI 0.49–0.62).

Conclusions: The UK 30 day unplanned hospital readmission model performed poorly in predicting readmission for the OPAT population at a US academic medical centre.

Background

Outpatient parenteral antimicrobial therapy (OPAT) is used for patients who require prolonged durations of IV antimicrobials and who are healthy enough to receive the medications in the outpatient setting. OPAT can reduce hospital stays and decrease healthcare expenditures.[1,2] OPAT has become increasingly common over the last three decades, with 1 in 1000 patients in the USA receiving OPAT annually.[3]

While OPAT is both efficacious and cost-effective, there are concerns with unplanned readmission in these patients, due in part to reductions in monitoring and supervision than if they were hospitalized.[4] The US Department of Health and Human Services (DHHS) Agency for Healthcare Research and Quality uses 30 day all-cause readmission as a patient-harm metric when calculating quality-of-care indicators.[5] These indicators are used to identify healthcare quality problem areas as well as for pay-for-performance initiatives.[5] In the published literature, 30 day all-cause readmission rates range from 6% to 26% in OPAT patients.[4,6–8]

The ability to identify OPAT patients at the highest risk of readmission would allow for more specific patient selection criteria and closer follow-up, which can minimize costs to the healthcare system and improve treatment outcomes.[9] In 2018, Durojaiye and colleagues[4] in the UK developed a 30 day unplanned readmission risk prediction model for OPAT patients based on six predictors available at the time of discharge: age, Charlson comorbidity score, number of prior hospitalizations in the preceding 12 months, concurrent receipt of more than one IV antimicrobial

© The Author(s) 2023. Published by Oxford University Press on behalf of British Society for Antimicrobial Chemotherapy.
This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial License (https://creativecommons.org/licenses/by-nc/4.0/), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited. For commercial re-use, please contact journals.permissions@oup.com

agent, type of infection, and mode of OPAT delivery (infusion centre, community nurse or self/caregiver administration). This model was externally validated through a retrospective cohort study of over 2500 OPAT patients at two health centres in the UK.[6] It was shown to have adequate discrimination ability in predicting patients with the occurrence of 30 day readmission (C-statistic 0.72, 95% CI 0.67–0.77).[6]

Significant differences in OPAT practice between the UK and the USA necessitate further validation prior to its application in the USA. In addition, factors that could impact unplanned readmission in our population (such as IV drug abuse and vancomycin use) were not included in the model. In the present study, we aimed to test the utility of the UK model and to identify centre-specific patient factors that may further improve the model.

Methods

Design/study population

This retrospective cohort study was reviewed and exempted by the Duke University Health System (DUHS) Institutional Review Board. Our primary objective was to determine the ability of the model by Durojaiye and colleagues[4] to discriminate patients entering the DUHS OPAT programme with 30 day unplanned (all-cause) readmission.[7] Our secondary objectives were to determine the ability of the UK model to differentiate patients with OPAT-related versus non-OPAT related readmissions, and evaluate the discriminatory ability of the UK model to predict 30 day unplanned readmissions with select factors added to the UK model.

Patients at least 18 years of age who were enrolled in the DUHS OPAT programme after being discharged from Duke University Medical Center or Duke Regional Hospital, a tertiary care hospital and a community hospital, respectively, between 1 July 2019 and 1 February 2020 (prior to the COVID-19 pandemic) were included. Patients were excluded if the planned OPAT duration was <7 days, they were lost to follow-up (defined as no documented medical contact after discharge), or if OPAT was initiated in the outpatient setting. Of note, the DUHS OPAT programme does not follow OPAT patients who have undergone transplantation, reside at a long-term acute care hospital, have a left ventricular assistance device, or receive renal replacement therapy.

Data collection

Potential study subjects were identified from the OPAT clinic database and screened for eligibility. For enrolled patients, data were gathered through the Duke Enterprise Data Unified Content Explorer (DEDUCE) and by review of the electronic medical record.[10] Study data were managed using REDCap (Research Electronic Data Capture) electronic data capture tools hosted at Duke University Hospital. REDCap is a secure, web-based software platform designed to support data capture for research studies.[11,12] Baseline demographics, OPAT-related characteristics (antibiotics, antibiotic-related adverse events, line access, microbiological culture results), 30 day readmissions (planned versus unplanned, OPAT versus non-OPAT related) and clinic follow-up were collected. DEDUCE was used to collect ICD-9 and ICD-10 codes, microbiological culture results, and all hospitalizations 12 months prior to and 30 days after the index admission (defined as the hospitalization resulting in discharge with OPAT) that were within DUHS. Weighted Charlson comorbidity scores were calculated based on patient ICD codes active within 12 months prior to the date of discharge from index admission into the OPAT programme.[13]

Statistical analysis

Prior literature recommends a minimum of 100 outcome events to provide adequate power for external validation of a prognostic model, and at least 10 events per regression coefficient.[4,14,15] The DUHS OPAT programme sees an average of 1000 patients a year. Assuming a 20% readmission rate, all patients within the stated 7 month study period were reviewed to ensure 100 outcome events. In the case of a patient with multiple OPAT episodes within the study period, a random selection of one OPAT episode per patient was used for the analysis.

The primary outcome was 30 day unplanned readmission, defined as any unplanned readmissions (to the same or another applicable acute care hospital) that happened for any reason within 30 days of discharge from the index admission.[8] The secondary outcome was 30 day unplanned OPAT-related hospitalization, defined as any unplanned readmissions (to the same or another applicable acute care hospital) thought to be due to failure or adverse events associated with OPAT or its administration as identified by readmission diagnosis within 30 days of discharge from the index admission.[8]

We followed the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) recommendations for reporting to externally validate the discriminative ability of the UK model to predict 30 day unplanned readmission on the DUHS data.[15] The UK model gives a linear predictor (LP) that can be converted to the probability of 30 day unplanned readmission for a patient discharged into the OPAT programme by $1/[1+\exp(-LP)]$. The LP is calculated by: $-3.628 + (0.016 \times \text{age in years}) + (0.264 \times \text{number of prior hospitalizations}) + (0.103 \times \text{Charlson comorbidity score}) + (0.248, \text{if self/caregiver administration}) + (0.479, \text{if infusion centre}) + (0.635, \text{if IV combination therapy}) + (0.480, \text{if endovascular infection}) - (0.337, \text{if respiratory disease}) + (0.189, \text{if urogenital infection}) - (0.037, \text{if bone and joint infection}) - (0.776, \text{if skin and soft tissue infection})$.[4,6,7]

The performance of the UK model was assessed with the scaled Brier score for overall model performance, the AUC (C-index) to visualize discrimination ability, calibration plot for calibration, and Hosmer–Lemeshow goodness-of-fit test for model fit.[16] The scaled Brier score can range from minus infinity to 1. A negative scaled Brier score means the forecast is less accurate than predicting using the average probability of the outcome. A scaled Brier score of 0 indicates it performs the same as predicting using the average probability of the outcome, whereas a score close to 1 indicates it performs much better than using the average probability of the outcome.

To assess whether recalibration was needed, we fit a logistic regression using 30 day unplanned readmission as the outcome and the LP as the only covariate. Recalibration was conducted by adjustment of the intercept, or so-called 'calibration in the large', and the slope, or so-called 'calibration slope' if they were significantly different from 0 and 1, respectively. The above analyses were repeated by using 30 day unplanned OPAT-related readmission as the outcome.

To evaluate the discriminatory ability of the UK model to predict 30 day unplanned readmission with the inclusion of select factors, a logistic regression model incorporating the LP and the select factors was fit.[17] Select factors that had been shown to be risk factors for readmission in other studies included OPAT delivery in a skilled nursing facility, vancomycin use and IV drug abuse.[7,18,19] Aminoglycoside use was to be an included select factor, but was not included as only one patient received it. Adjusted ORs (aORs) of the additional variables were reported with 95% CIs. The same performance metrics were assessed for the updated model.

Individual predictors in the UK model and the select factors were compared between groups using two-sample *t*-tests for continuous variables and chi-squared tests or Fisher's exact tests, where appropriate, for categorical variables. Statistical significance was assessed at a level of 0.05 without accounting for multiple testing. All statistical analyses were conducted in SAS 9.4 (SAS Institute, Cary, NC, USA) and R 4.0.0 (R Core Team, Vienna, Austria).

Results

A total of 574 patients were identified from the DUHS OPAT database, with 606 distinct OPAT encounters. After exclusion and

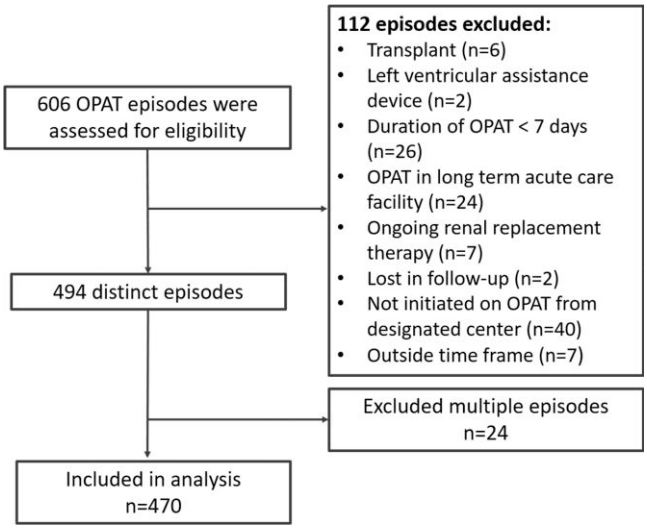

Figure 1. Methods flow diagram.

removal of multiple episodes, 470 unique patients were included in the analysis (see Figure 1). Comparing the baseline characteristics included in the UK model of the DUHS cohort versus the UK derivation cohort, DUHS patients tended to be older (mean age 60.4 versus 56.8 years, $P < 0.001$) and had a higher Charlson comorbidity score (median 3 versus 1) (Table 1). Differences in primary treatment indications for the DUHS cohort compared with the UK cohort were for bone and joint infections (58.7% versus 12.8%) and skin and soft tissue infection (7% versus 57.4%), respectively. The mode of delivery of OPAT varied between the two cohorts, with the entire DUHS cohort administering antimicrobials at home (71.3%) or in a skilled nursing facility (28.7%), while the majority of the UK cohort received antimicrobials in an infusion clinic (71.5%) and no patients received OPAT in a skilled nursing facility. Additional variables were collected (such as microbiology results) but not incorporated into the model (Table S1, available as Supplementary data at *JAC-AMR* Online).[9]

For the primary outcome measure, the rates of 30 day (all-cause) unplanned readmission were 20% versus 11.5%

Table 1. Characteristics of subjects in UK and DUHS cohorts

	UK study cohort[a] *N* = 1073	DUHS cohort *N* = 470	*P* value
Variable			
Age at hospital admission, years, mean (SD)	56.8 (17.5)	60.4 (16.1)	<0.001
Male gender, *n* (%)	611 (56.9)	282 (60)	0.29
System indicated for OPAT treatment, *n* (%)			<0.001
skin/soft tissue	616 (57.4)	33 (7)	
bone and joint	137 (12.8)	276 (58.7)	
urogenital	70 (6.5)	23 (4.9)	
respiratory	45 (4.2)	15 (3.2)	
endovascular	45 (4.2)	64 (13.6)	
other[b]	160 (14.9)	59 (12.6)	
Charlson comorbidity score, median (IQR)	1 (0–2)	3 (1–5)	Not assessed
Non-OPAT hospitalizations in preceding year, median (IQR)	0 (0–1)	0 (0–1)	Not assessed
Mode of OPAT delivery, *n* (%)			<0.001
home (self/caregiver)	105 (9.8)	335 (71.3)	
infusion centre	767 (71.5)	0 (0)	
community nurse	201 (18.7)	0 (0)	
skilled nursing facility	0 (0)	135 (28.7)	
Concurrent IV antibiotics during OPAT (two or more), *n* (%)	81 (7.5)	88 (18.7)	<0.001
Outcomes			
Unplanned readmission during 30 day post-index discharge, *n* (%)	123 (11.5)	94 (20)	<0.001
Unplanned OPAT-related readmission during 30 day post-index, *n* (%)	72 (6.7)	56 (11.9)	<0.001
Reasons for OPAT-related readmission during 30 day post-index, *n* (%)			Not assessed
infection-related (worsening infection/new infection)	60 (83.3)	30 (53.5)	
antibiotic-related adverse effects	7 (9.7)	17 (30.3)	
IV access-related	3 (4.2)	2 (3.6)	
other	2 (2.8)	7 (12.5)	
Discharge to first unplanned readmission, days, mean (SD)	Not assessed	12.1 (8)	
Emergency room visit during 30 day post-index, *n* (%)	Not assessed	76 (16.2)	
OPAT-related emergency room visit during 30 day post-index, *n* (%)	Not assessed	44 (9.4)	

[a]Data from Durojaiye *et al.*[6]
[b]Includes intra-abdominal infection, CNS infection, bloodstream infection (catheter-associated, unknown source etc.).

Table 2. Model characteristics of DUHS patients according to 30 day unplanned readmission

	No 30 day unplanned readmission $N=376$	Had 30 day unplanned readmission $N=94$	P value $N=470$
Age at admission, years, mean (SD)	60.8 (15.6)	58.6 (17.9)	0.23[a]
≤30, *n* (%)	19 (5.1)	5 (5.3)	
31–40, *n* (%)	29 (7.7)	12 (12.8)	
41–50, *n* (%)	34 (9)	11 (11.7)	
51–60, *n* (%)	91 (24.2)	25 (26.6)	
61–70, *n* (%)	88 (23.4)	15 (16)	
>70, *n* (%)	115 (30.6%)	26 (27.7%)	
Charlson comorbidity score, mean (SD)	3.3 (2.7)	3.7 (2.9)	0.31[a]
0, *n* (%)	55 (14.6)	15 (16)	
1, *n* (%)	47 (12.5)	8 (8.5)	
2, *n* (%)	71 (18.9)	17 (18.1)	
3, *n* (%)	62 (16.5)	10 (10.6)	
4+, *n* (%)	141 (37.5)	44 (46.8)	
Hospitalizations in the prior 12 months, mean (SD)	0.9 (1.3)	0.9 (1.2)	0.76
Initial location of OPAT administration, *n* (%)			0.52
home (self/caregiver)	265 (70.5)	70 (74.5)	
skilled nursing facility	111 (29.5)	24 (25.5)	
infusion centre	0 (0)	0 (0)	
Concurrent IV antibiotics during OPAT (two or more) , *n* (%)	72 (19.1)	16 (17)	0.75
Indication of OPAT, *n* (%)			0.96
bone or joint infection	222 (59)	54 (57.4)	
endovascular infection	49 (13)	15 (16)	
skin and soft tissue infection	26 (6.9)	7 (7.4)	
respiratory disease	13 (3.5)	2 (2.1)	
urogenital infection	18 (4.8)	5 (5.3)	
other indication	48 (12.8)	11 (11.7)	
Aminoglycoside used for OPAT, *n* (%)	1 (0.3)	0 (0)	Not assessed
Vancomycin used for OPAT, *n* (%)	141 (37.5)	29 (30.9)	0.32
IV drug abuse, *n* (%)	19 (5.1)	5 (5.3)	>0.99

[a]Age and Charlson comorbidity score were compared as continuous variables between groups.
Continuous variables were compared using two-sample *t*-tests, and categorical variables were compared using chi-squared tests or Fisher's exact tests where appropriate.

($P<0.001$) in the DUHS and UK cohorts, respectively (Table 1). In the DUHS cohort, 59.5% of the unplanned readmissions were deemed OPAT-related. Of those, the majority were infection-related (such as worsening infectious symptoms or new infection) or antibiotic adverse effects (such as acute renal injury or neutropenia). Baseline model characteristics between patients with unplanned readmission and those without were very similar, with none reaching statistical significance (Table 2).

Table 3 summarizes the performance of the three models tested. Figure 2(a) shows the receiver operating curve, and Figure 3(a) shows the calibration plot of the UK model for predicting 30 day unplanned readmission in the DUHS cohort. The C-statistic was 0.52 (95% CI 0.46–0.59), indicating the UK model did not perform better than random guessing in the DUHS cohort. The Hosmer–Lemeshow test ($P<0.001$, low P value indicates poor fit) and the calibration slope (0.06, 95% CI −0.28 to 0.38; slope of 1 indicates agreement) both suggested a poor agreement between predicted and observed probabilities of 30 day unplanned readmission. The scaled Brier score was negative, indicating the forecast was less accurate than predicting using the average probability of the outcome (i.e. the observed readmission rate in the DUHS cohort, 0.2). After recalibration, the model had better fit (Hosmer–Lemeshow test $P=0.33$), but discrimination ability remained poor (C-statistic 0.52, 95% CI 0.46–0.59). When looking at the probabilities for each patient, we found the model generally overestimated risk of readmission (Figure S1).

We did not observe statistically significant differences in additional risk factors added to the model and they were not predictive of 30 day unplanned readmission (Table 2, Table S2). Figure 2(b) shows the receiver operating curve and Figure 3(b) shows the calibration plot of the updated model for predicting 30 day unplanned readmission in the DUHS cohort. The C-statistic was 0.55 (95% CI 0.49–0.62), indicating the updated model did not perform better than the UK model in the DUHS cohort (Table 3). The LP in the new model did not differ significantly between those with and without readmission (predictor aOR 1.08, 95% CI 0.77–1.51) (Table 3). Figure 2(c) shows the receiver

Table 3. Effect sizes (in terms of aOR) and goodness-of-fit statistics

	Original UK model for unplanned readmission[a]			UK model with additional variables for unplanned readmission[a]			Original UK model for unplanned OPAT-related readmission[a]		
Predictors	aOR	95% CI	*P* value	aOR	95% CI	*P* value	aOR	95% CI	*P* value
UK linear predictor	—	—	—	1.08	(0.77–1.51)	0.66	—	—	—
Vancomycin use	—	—	—	0.77	(0.47–1.23)	0.28	—	—	—
IV drug abuse	—	—	—	1.08	(0.35–2.84)	0.88	—	—	—
OPAT delivered in a skilled nursing facility	—	—	—	0.82	(0.48–1.36)	0.45	—	—	—
Model performance									
Discrimination, C-statistic	0.52	(0.46–0.59)	—	0.55	(0.49–0.62)	—	0.55	(0.47–0.64)	—
Hosmer–Lemeshow (df)	47.54 (8)	—	<0.001	7.04 (8)	—	0.53	60.2 (8)	—	<0.001
Scaled Brier score	−0.07	—	—	0	—	—	−0.36	—	—
Calibration slope	0.06	(−0.28 to 0.38)	—	1	(−0.39 to 2.43)	—	−0.33	(−0.77 to 0.09)	—
Calibration in the large	−1.29	(−1.9 to −0.72)	—	0	(−1.94 to 1.97)	—	−2.57	(−3.43 to −1.8)	—
After recalibration									
Discrimination, C-statistic	0.52	(0.46–0.59)	—	—	—	—	0.55	(0.47–0.64)	—
Hosmer– Lemeshow (df)	9.14 (8)	—	0.33	—	—	—	10.1 (8)	—	0.35
Scaled Brier score	0	—	—	—	—	—	0.35	—	—

[a]Model from Durojaiye *et al*.[6]
df, degrees of freedom.

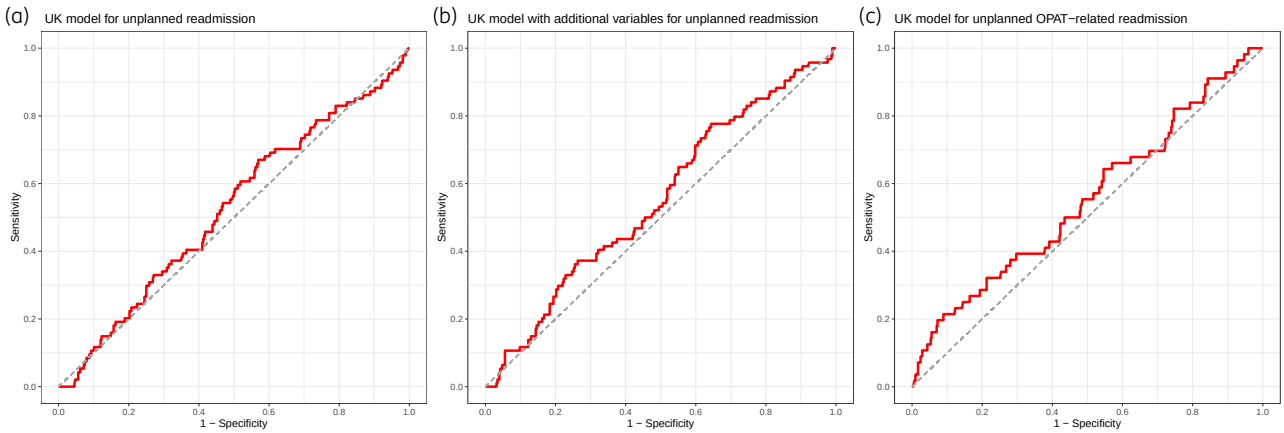

Figure 2. Receiver operating curves (ROCs) of the models evaluated. (a) UK model for unplanned readmission. (b) UK model with additional variables for unplanned readmission. (c) UK model for unplanned OPAT-related readmission. The dashed line on the diagonals indicates no discrimination ability.

operating curve and Figure 3(c) shows the calibration plot of the UK model for predicting 30 day unplanned OPAT-related readmission in the DUHS cohort. The model performance tests again suggested a poor agreement between predicted and observed probabilities of 30 day unplanned OPAT-related readmission. We also observed a negative scaled Brier score, indicating the forecast was less accurate than predicting using the average probability of the outcome (i.e. the observed 30 day unplanned OPAT-related readmission rate, 0.119). After recalibration, the model fit better (Hosmer–Lemeshow test $P=0.35$), but discrimination ability remained poor (C-statistic 0.55, 95% CI 0.47–0.64).

Discussion

OPAT is an essential service that helps decrease hospital length of stay and provides a less costly alternative for patients needing longer durations of IV antibiotics.[1,3] However, OPAT patients are medically complex and at risk for hospital readmission and adverse effects from antimicrobials. Being able to identify the highest risk OPAT patients is essential. Multiple readmission models have been developed to identify the highest risk OPAT patients, but there are limited data regarding the generalizability of these models for use in another institution.[4,8,19] The UK model has the most robust data, including a published external validation of

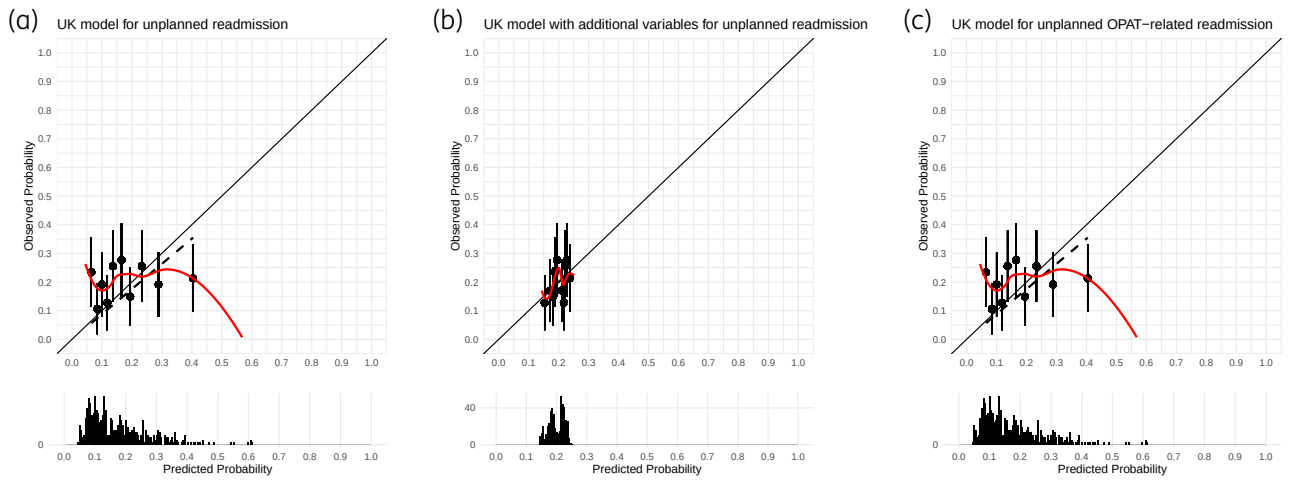

Figure 3. Calibration plots of the models evaluated. (a) UK model for unplanned readmission. (b) UK model with additional variables for unplanned readmission. (c) UK model for unplanned OPAT-related readmission. The black solid line indicates perfect calibration. The black dashed line shows the straight-line fit of predictions from the model, and the red solid line shows the locally estimated scatterplot smoothing (LOESS) fit of the predictions from the model. The circled points represent observed proportions of outcomes in decile groups of predicted probabilities, with vertical lines representing 95% CI. The histogram on the *x*-axis summarizes the distribution of patients in the range of predicted probabilities of the outcome.

another UK population, and a higher C-statistic than other models, which is why it was chosen to be tested in the DUHS OPAT population.[6,8]

Our study assessed the discriminative ability of the established 30 day unplanned hospital readmission risk assessment model for adult patients receiving OPAT at DUHS. While the rate of unplanned readmission was significantly higher in the DUHS cohort than in the original UK model (20.3% versus 11.2%), it was comparable to other studies.[6–8] Of note, the primary outcome of this study was slightly different than in the original model studies. The UK model looked at 30 day unplanned readmission, defined as 30 days from discharge from the OPAT programme (and inclusive of all days in the programme post-discharge from index admission) rather than 30 days from discharge from index admission. We chose a narrower endpoint of 30 days from discharge from index admission as this is how the DHHS determines reimbursement based on readmissions, and this is the period of highest readmission rates within OPAT populations.[5,7,9] Our endpoint was inclusive of the endpoint in the UK model, but we may have missed patients with unplanned readmissions further out in therapy.

Overall, all measures of model validity show the original UK model was not able to discriminate between patients with readmissions and those without. When assessing only patients with OPAT-related readmission, the model was still not discriminative and could not predict risk of readmission. The model's performance was also poor when incorporating additional predictors. Multiple predictors of readmission in the model that were significant in the UK population were not significant in this review.[4,7] Neither age, receipt of concurrent IV antibiotics, number of prior hospitalizations, nor type of infection influenced 30 day readmission. The additional predictors that had been risk factors in other studies such as vancomycin use, OPAT delivered via skilled nursing facility, and IV drug abuse were not different between patients with readmission and those without.[7,18,19] The only assessed variable that reached significance was follow-up in OPAT clinic. The reason this was not included in the model is because we were only able to record completed visits, and there is an inherent bias in that patients who were already readmitted missed OPAT clinic visits and thus were not captured. One review has found that early follow-up to OPAT clinic reduces readmission rates, and a readmission prediction model could be used to identify which patients need closer follow-up.[9]

Decreases in the performance of a model are common in external validation studies, often caused by differences in case mix and patient population, overfitting of the model, and difference in the effect of model predictors. While we attempted to address this by adding additional predictors to the updated model and recalibrating the model, ultimately it was still not able to predict readmission well. There are multiple possible reasons why the UK model was not effective in the DUHS cohort. First, the DUHS cohort had more comorbidities and more deep-seated infections than the UK cohort. Forty percent of unplanned readmissions in the DUHS cohort were due to non-OPAT reasons, such as heart failure exacerbation. In the original two UK cohorts, non-OPAT unplanned readmission was 28.6% and 40.7% of all unplanned readmissions, the latter of which is similar to our study.[4,6] Second, the majority of the patients in the UK cohort received antibiotics at an infusion clinic, while patients in the DUHS cohort received antibiotics either at a skilled nursing facility or at home. Patients discharged to a skilled nursing facility are less likely to be medically optimized compared with patients who are able to come to an infusion clinic, and patients who self-administer antibiotics at home do not undergo the same monitoring as patients who receive antibiotics at an infusion clinic.

Some limitations to this study are worth noting. The retrospective nature of the study introduces the potential for reduced accuracy of recorded data. Patients who had readmissions outside of the DUHS network would have been missed. However, most

outside readmissions would have been captured during follow-up with the OPAT clinic, and patients lost after discharge from index admission were excluded. The determination of some secondary characteristics, such as OPAT- versus non-OPAT-related admission was done via the discretion of the reviewing clinician. While there were strict review methods followed in collection, these secondary characteristics were more prone to error/bias.

Conclusions

The prediction model established by Durojaiye and colleagues was not able to reliably discriminate the risk of 30 day unplanned (all-cause) readmission in DUHS patients receiving OPAT. Further research should focus on development of unique models as well as validation of existing ones.

Acknowledgements

Partial results were presented as a poster presentation at IDWeek 2022 (poster number 1025).

Funding

Research reported in this publication was supported by the National Center for Advancing Translational Sciences of the National Institutes of Health under Award Number UL1TR002553. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. This research received no other specific funding from any funding agency in the public, commercial, or not-for-profit sectors.

Transparency declarations

Potential Conflict of Interest: All authors deny any conflict of interest relevant to this manuscript.

Patient Consent Statement: Patient consent not required.

Supplementary data

Figure S1 and Tables S1 and S2 are available as Supplementary data at *JAC-AMR* Online.

References

1 Williams DN, Baker CA, Kind AC *et al*. The history and evolution of outpatient parenteral antibiotic therapy (OPAT). *Int J Antimicrob Agents* 2015; **46**: 307–12.

2 Norris AH, Shrestha NK, Allison GM *et al*. 2018 Infectious Diseases Society of America clinical practice guideline for the management of outpatient parenteral antimicrobial therapy. *Clin Infect Dis* 2019; **68**: e1–e35. https://doi.org/10.1093/cid/ciy867

3 Tice AD, Rehm SJ, Dalovisio JR *et al*. Practice guidelines for outpatient parenteral antimicrobial therapy. *Clin Infect Dis* 2004; **38**: 1651–72. https://doi.org/10.1086/420939

4 Durojaiye OC, Kritsotakis EI, Johnston P *et al*. Developing a risk prediction model for 30-day unplanned hospitalization in patients receiving outpatient parenteral antimicrobial therapy. *Clin Microbiol Infect* 2019; **25**: e1–e7. https://doi.org/10.1016/j.cmi.2018.11.009

5 Agency for Healthcare Research and Quality. Quality Indicator Empirical Methods, v2021. 2021. https://qualityindicators.ahrq.gov/Downloads/Resources/Publications/2021/Empirical_Methods_2021.pdf.

6 Durojaiye OC, Morgan R, Chelaghma N *et al*. External validity and clinical usefulness of a risk prediction model for 30 day unplanned hospitalization in patients receiving outpatient parenteral antimicrobial therapy. *J Antimicrob Chemother* 2021; **76**: 2204–12. https://doi.org/10.1093/jac/dkab127

7 Huang V, Ruhe JJ, Lerner P *et al*. Risk factors for readmission in patients discharged with outpatient parenteral antimicrobial therapy: a retrospective cohort study. *BMC Pharmacol Toxicol* 2018; **19**: 50. https://doi.org/10.1186/s40360-018-0240-3

8 Allison GM, Muldoon EG, Kent DM *et al*. Prediction model for 30-day hospital readmissions among patients discharged receiving outpatient parenteral antibiotic therapy. *Clin Infect Dis* 2014; **58**: 812–9. https://doi.org/10.1093/cid/cit920

9 Saini E, Ali M, Du P *et al*. Early infectious disease outpatient follow-up of outpatient parenteral antimicrobial therapy patients reduces 30-day readmission. *Clin Infect Dis* 2019; **69**: 865–8. https://doi.org/10.1093/cid/ciz073

10 Horvath MM, Rusincovitch SA, Brinson S *et al*. Modular design, application architecture, and usage of a self-service model for enterprise data delivery: the Duke Enterprise Data Unified Content Explorer (DEDUCE). *J Biomed Inform* 2014; **52**: 231–42. https://doi.org/10.1016/j.jbi.2014.07.006

11 Harris PA, Taylor R, Thielke R *et al*. Research electronic data capture (REDCap) – a metadata-driven methodology and workflow process for providing translational research informatics support. *J Biomed Inform* 2009; **42**: 377–381. https://doi.org/10.1016/j.jbi.2008.08.010

12 Harris PA, Taylor R, Minor BL *et al*. The REDCap consortium: building an international community of software partners. *J Biomed Inform* 2019; **95**: 103208. https://doi.org/10.1016/j.jbi.2019.103208

13 Glasheen WP, Cordier T, Gumpina R *et al*. Charlson comorbidity index: ICD-9 update and ICD-10 translation. *Am Health Drug Benefits* 2019; **12**: 188–97.

14 Collins GS, Ogundimu EO, Altman DG. Sample size considerations for the external validation of a multivariable prognostic model: a resampling study. *Stat Med* 2016; **35**: 214–26. https://doi.org/10.1002/sim.6787

15 Moons KG, Altman DG, Reitsma JB *et al*. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): explanation and elaboration. *Ann Intern Med* 2015; **162**: W1–73. https://doi.org/10.7326/M14-0698

16 Steyerberg EW, Vickers AJ, Cook NR *et al*. Assessing the performance of prediction models: a framework for traditional and novel measures. *Epidemiology* 2010; **21**: 128–38. https://doi.org/10.1097/EDE.0b013e3181c30fb2

17 Janssen KJ, Moons KG, Kalkman CJ *et al*. Updating methods improved the performance of a clinical prediction model in new patients. *J Clin Epidemiol* 2008; **61**: 76–86. https://doi.org/10.1016/j.jclinepi.2007.04.018

18 Means L, Bleasdale S, Sikka M *et al*. Predictors of hospital readmission in patients receiving outpatient parenteral antimicrobial therapy. *Pharmacotherapy* 2016; **36**: 934–9. https://doi.org/10.1002/phar.1799

19 Keller SC, Wang N-Y, Salinas A *et al*. Which patients discharged to home-based outpatient parenteral antimicrobial therapy are at high risk of adverse outcomes? *Open Forum Infect Dis* 2020; **7**: ofaa178. https://doi.org/10.1093/ofid/ofaa178