Development and evaluation of prediction models to improve the hospital appointments overbooking strategy at a large tertiary care hospital in Sultanate of Oman

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Abstract

Background

Missed a hospital appointments are common in routine outpatient settings and have a negative effect, both clinically and financially. The aim of this study was to develop prediction models for missed hospital appointments and evaluate different approaches of overbooking.

Methods

A retrospective analysis was conducted using outpatient clinic appointments at The Royal Hospital, Muscat, Sultanate of Oman. Prediction models, using logistic regression, were developed for the whole cohort and for each clinic separately, to predict missed hospital appointments. Performance was evaluated in a holdout set. Finally, we performed a simulation comparing the use of the prediction model to overbook against systematic overbooking.

Results

Our dataset included 947,364 scheduled outpatient appointments in which 201,877 (21.3%) were missed. The missed hospital appointment rates varied by clinic, ranging from 13.8% for Oncology to 28.3% for Urology. The whole cohort model achieved an AUC of 0.771 (95% CI: 0.768-0.775), whereas individual clinical model AUCs ranged from 0.845 (95% CI: 0.836-0.855) for Oncology to 0.738 (95% CI: 0.732-0.744) for Paediatrics. The overbooking approach using clinic-specific predictive model outperformed the systematic overbooking approach resulted in maximum underutilise of available appointments ranged from 10.4% in Oncology clinic to 25.0% in Gastroenterology clinic.

Conclusion

Prediction models can be used to predict the probability of a patient missing a hospital appointment with good accuracy. These prediction models could be used in an overbooking strategy which allows for extra appointments to be scheduled without overburdening the clinics, thus reducing the impact of missed hospital appointments.

Keywords: Hospital appointments, Prediction model, Overbooking, Simulation,

1. Background

One of the global challenges in any healthcare system is hospital appointment nonattendance. The rate of missed appointment varies around the world, ranging between 14.9% (Europe) and 27.1% (North America)[1,2], and across healthcare settings. Missed hospital appointments affect the ability of the healthcare facility to provide a good service, leading to patient dissatisfaction; increased waiting times and therefore increased morbidity and mortality.[3] In the UK, £216 million is the estimated annual cost as a result of one million missed GP appointments every month.[4] With rising costs and increasing demands of health care systems, there is a need to utilize available recourses to provide quality care to all patients.[5,6]

Clinical prediction models (CPMs) can be used to predict people at risk of developing certain diseases, predicting disease prognosis and adverse outcomes.[7] They have shown a positive impact in reducing cost, assisting in better decision making for patient heath, allocation of resources and effective utilisation of medical services.[8] Prediction models have been used widely to identify patients with higher risk of missing their hospital appointments. A systematic review including 50 articles showed an increase in the use of such models in the last 10 years by 82% across a range of healthcare settings.[9]

Prediction models are used in UK hospitals to guide appointment strategies and it has been reported that the NHS could save millions using such models.[10,11] Several prediction models for missed appointments have been developed with Area under the receiver operating characteristic curve (AUC) ranging from 0.60 to 0.86.[12,13] These studies use data from a single hospital clinic and were conducted in developed countries [14,15]

Missed hospital appointments are also a major concern for the Royal hospital, Sultanate of Oman, which has an extremely high percentage of missed appointments (22.3% overall and up to 30.3% in Urology clinic). Hence, there is need to implement interventions to reduce the impact of the problem.[16] To our knowledge, no study has developed a prediction model for missed hospital appointments in Oman, but there is opportunity to do so as electronic health record data are available. In this study we aimed to: 1) develop and validate prediction models for missed hospital appointments using the routinely collected data within the patient's electronic medical records

(EMR); and illustrate, through a simulation, the use of the developed prediction models in managing overbooking and compare to systematic overbooking approach being used within the hospital currently.

2. Methods

2.1 Data

Appointment data were extracted from the hospital health information management (ALSHIFA) system, a patient electronic medical record system[17]. All scheduled outpatients appointments were extracted between January 2014 and February 2021 from The Royal Hospital, the largest tertiary referral hospital in the capital city of Muscat, Sultanate of Oman. The data did not include cancelled appointments or rescheduled appointments and walk-in appointments made within the emergency department. From the complete dataset, we split the data by clinics as follows: One overall dataset including all clinics except the Paediatric and Obstetrics clinics due to distinct populations; one dataset for Paediatric clinic; one dataset for the Obstetrics and Gynaecology clinic; and a dataset for each of the remaining five clinics in the overall dataset (Surgery, Urology, Oncology, Gastroenterology, and Diabetic and Endocrine clinic).We applied the data cleaning process as previously described by Alawadhi et al.[18,16]

2.2 Statistical analysis

2.2.1 Risk prediction model

Logistic regression models were developed to predict the risk of missed hospital appointments in each dataset separately. For each clinic specific dataset, patients were randomly divided into a development and validation cohort (80% and 20%, respectively). The development and validation cohorts for Diabetic and Endocrine, Surgery, Urology, Oncology and Gastroenterology clinics were combined to generate the development and validation cohorts for the overall model, respectively. This was to ensure that all models were developed and validated on the same data, such that the development data from each clinic was also used as development data for the individual clinics. Development data were used to fit the model and each developed model was validated in its associated validation data.

Information on gender, appointment day and month, marital status, governorate (place of residence), appointment waiting time, nationality, and service cost (patient contribution to medical service based on age, nationality and monthly income) were included in model development. Appointments were categorised as attended if the patient's visit was created and logged in the system and missing otherwise. All variables were considered linear except age, where fractional polynomials were used.[19]

Performance of the models were evaluated by computing the area under the receiver operating characteristic curve (AUC) , mean squared error, percentage of correct prediction (PCP), calibration slope and calibration intercept (calibration-in-the-large).[20,21 22,23 24] Calibration curves were also produced.

2.2.2 Simulating different overbooking approaches for appointment scheduling

Following model development and validation, a simulation study was performed to compare a range of overbooking approaches that could be used in clinical practice and investigate if there is possible added value of using prediction models in overbooking strategies. First, the average number of daily appointments was calculated for each dataset (Supplementary Table 2) and this was used to define the number of available daily appointments. Then a random sample of data was extracted based on this average and a systematic overbooking simulation was performed, overbooking by 5%, 10%, 15%, 20%, 25%, 30%, 35% and 40%. The systematic overbooking approach was compared to an overbooking approach that used the prediction model where patient-specific probabilities were estimated and the number of missed appointments predicted in each sample were used to determine the overbooking percentage.

The simulation was performed 1000 times for dataset. Within each iteration, the difference between the number of available and the number of patients who attended, after applying overbooking, was calculated. A positive value indicated that the number of available appointments exceeded attended appointments (clinic underutilised); a negative value indicated that the number of attended appointments exceeded the number of available appointments (clinic overburdened) and zero indicated that the attended appointments were equal to available appointments. The difference between attended appointments and available appointments was converted to a percentage of appointments available, allowing comparison of approaches across clinics. The mean, median, 2.5% percentile and 97.5% percentile for the difference between attended appointments and available appointments was calculated across the 1000 iterations.

3. Results

3.1 Baseline characteristics of the final dataset used in the study

There were 947,364 appointments in the final dataset, of which 201,877 (21.3%) were missed. The dataset included 576,127 (60.8%) female patients and the mean age was 31 years old (Table 1). The rate of missed appointments was high for patients with waiting times less than 30 days and more than 120 days (17.2%, 26.6%, respectively). Patients with social affair coverage missed 16.8% of their hospital appointment (4229) whereas patients who had to pay their visit and registration fees missed 21.3% of their hospital appointments (175,026). The rate of missed hospital appointments varied across clinics ranging from 13.8% in Oncology to 28.3% in Urology. Supplementary Table 3 shows more details about the characteristics of patients within specific clinics.

Table 1: Characteristics of the complete dataset and stratified by attended and missed appointments

	Overall N (%)	Attended N (%)	Missed N (%)
	947364 (100)	745487 (78.7)	201877 (21.3)
Sex			
Female	576127 (60.8)	459053 (79.7)	117074 (20.3)
Male	371237 (39.2)	286434 (77.2)	84803 (22.8)
Age (mean(SD))	36 (21)	35 (21)	37 (22)
Appointment day			
Sunday	195859 (20.7)	151761 (77.5)	44098 (22.5)
Monday	195169 (20.6)	154070 (78.9)	41099 (21.1)
Tuesday	195560 (20.6)	155172 (79.3)	40388 (20.7)
Wednesday	195784 (20.7)	153109 (78.2)	42675 (21.8)
Thursday	164992 (17.4)	131375 (79.6)	33617 (20.4)
Appointment month			
January	93745 (9.9)	74871 (79.9)	18874 (20.1)
February	88193 (9.3)	71588(81.2)	16605 (18.8)
March	84353 (8.9)	67690 (80.2)	16663 (19.8)
April	80481 (8.5)	63339 (78.7)	17142 (21.3)
May	82685 (8.7)	63726 (77.1)	18959 (22.9)
June	66941 (7.1)	50765 (75.8)	16176 (24.2)
July	67491 (7.1)	52282 (77.5)	15209 (22.5)
August	70167 (7.4)	54240 (77.3)	15927 (22.7)
September	73769 (7.8)	58359 (79.1)	15410 (20.9)
October	82052 (8.7)	64986 (79.2)	17066 (20.8)

November	75444 (8.0)	58908 (78.1)	16536 (21.9)
December	82043 (8.7)	64733 (78.9)	17310 (21.1)
Marital status			
Child (<13Years Old)	175840 (18.6)	141414 (80.4)	34426 (19.6)
Single	150817 (15.9)	116935 (77.5)	33882 (22.5)
Married	509016 (53.7)	403611 (79.3)	105405 (20.7)
Divorced	4270 (0.5)	3264 (76.4)	1006 (23.6)
Widow	6471 (0.7)	4894 (75.6)	1577 (24.4)
Missing	100950 (10.7)	75369 (74.7)	25581 (25.3)
Governorate			
Muscat	516920 (54.6)	402978 (78.0)	113942 (22.0)
South Batina	13884 (1.5)	10469 (75.4)	3415 (24.6)
AL Dhakiliya	5024 (0.5)	3762 (74.9)	1262 (25.1)
North Batina	10762 (1.1)	8094 (75.2)	2668 (24.8)
North Sharqiya	83563 (8.8)	68488 (82.0)	15075 (18.0)
South Sharqiya	84192 (8.9)	67028 (79.6)	17164 (20.4)
AL Dhahira	91251 (9.6)	73226 (80.2)	18025 (19.8)
AL Buriami	50387 (5.3)	38790 (77.0)	11597 (23.0)
AL Wusta	47766 (5.0)	37769 (79.1)	9997 (20.9)
Musandam	39056 (4.1)	31464 (80.6)	7592 (19.4)
Dhofar	4440 (0.5)	3325 (74.9)	1115 (25.1)
GCC Countries	119 (0.0)	94 (79.0)	25 (21.0)
Service cost			
Pay visit and registration fees only[¥]	822065 (86.8)	647039 (78.7)	175026 (21.3)
<2 Years old*	68092 (7.2)	53542 (78.6)	14550 (21.4)
Pay all medical service fees[†]	31978 (3.4)	23906 (74.8)	8072 (25.2)
Under Social Affair coverage*	25229 (2.7)	21000 (83.2)	4229 (16.8)
Appointment waiting group			
< 30 Days	365400 (38.6)	302386 (82.8)	63014 (17.2)
> 30 ≤ 60 Days	143100 (15.1)	112852 (78.9)	30248 (21.1)
> 60 ≤ 90 Days	122282 (12.9)	95433 (78.0)	26849 (22.0)
> 90 ≤ 120 Days	91011 (9.6)	69352 (76.2)	21659 (23.8)
> 120 Days	225571 (23.8)	165464 (73.4)	60107 (26.6)
Nationality			
Omani	901263 (95.1)	710802 (78.9)	190461 (21.1)
Non-Omani	46101 (4.9)	34685 (75.2)	11416 (24.8)
Prior visit group			
Zero prior appointment	196293 (20.7)	98469 (50.2)	97824 (49.8)
One prior appointment	135590 (14.3)	99596 (73.5)	35994 (26.5)
Two prior appointments	97431 (10.3)	79616 (81.7)	17815 (18.3)
Three prior appointments	74281 (7.8)	63841 (85.9)	10440 (14.1)
Four prior appointments	58872 (6.2)	52181 (88.6)	6691 (11.4)
Five prior appointments	47752 (5.0)	43039 (90.1)	4713 (9.9)
> Five prior appointments	337145 (35.6)	308745 (91.6)	28400 (8.4)

The distribution for characteristics is displayed vertically for overall observations and horizontally for stratification by attended and missed hospital appointments.

¥ Omani citizens, GCC citizens, Expatriate works for government. Expatriate married to Omani.

* Exempted from visit and registration fees.

†Expatriates pay all medical fees (service fees, visit fees, registration fees).

3.2 Prediction model results

The performance of the overall model and models by clinics varied. The AUC of the overall model was 0.771(95% CI: 0.768-0.775). The Oncology and Obstetrics and Gynaecology clinic models had the highest AUCs of 0.845 (95% CI: 0.836-0.855) and 0.805 (95% CI: 0.799-0.812), respectively, where the performance for Paediatrics was slightly lower (AUC 0.738(95% CI: 0.732-0.744)). The number of appointments in the development and validation datasets for the overall model and by clinic is displayed in supplementary table 1.

The calibration curves for all models can be found in Figure 1. The calibration slope and calibration intercept was variable between models for individual clinics. The Surgery clinic calibration slope and intercept were 1.038 (95% CI: 1.001-1.076) and 0.006 (95% CI: -0.032-0.045), respectively, and the Gastroenterology clinic model had slope of 0.987 (95% CI: 0.932-1.043) and intercept of 0.001(95% CI: -0.060-0.061). The overall model had a calibration slope of 0.994 (95% CI: 0.979-1.009) with calibration intercept of -0.003 (95% CI: -0.018-0.012). See Table 2 for more details.

Table 2: Predictive performance for each model when applied to the validation data

Model	AUC (95% CI)	Accuracy	Calibration slope (95% CI)	Calibration Intercept (95% CI)	MSE	PCP
Overall model†	0.771 (0.768, 0.775)	77.29%	0.994 (0.979, 1.009)	-0.003 (-0.018,0.012)	0.142	0.714
Diabetic & Endocrine	0.764 (0.757, 0.772)	76.91%	0.986 (0.954, 1.019)	0.019 (-0.013, 0.053)	0.153	0.699
Surgery	0.791 (0.783, 0.799)	78.29%	1.038 (1.001, 1.076)	0.006 (-0.034, 0.045)	0.136	0.721
Urology	0.795 (0.785, 0.805)	79.58%	0.973 (0.930, 1.016)	-0.049 (-0.097, -0.001)	0.148	0.698
Oncology	0.845 (0.836, 0.855)	85.24%	0.972 (0.934, 1.012)	-0.009 (-0.064, 0.046)	0.087	0.828
Gastroenterology	0.790 (0.778, 0.802)	79.32%	0.987 (0.932, 1.043)	0.001 (-0.060, 0.061)	0.151	0.702
Paediatric	0.738 (0.732, 0.744)	73.89%	0.996(0.967, 1.025)	-0.0004 (-0.026, 0.025)	0.140	0.719
Obstetrics and Gynaecology	0.805 (0.799, 0.812)	81.08%	0.971(0.942, 0.999)	0.017 (-0.016, 0.050)	0.111	0.780

†Includes all clinics except Paediatric clinic and Obstetrics & Gynaecology clinic. AUC: Area under the ROC curve: an aggregated metric that evaluate how well a logistic regression model classifies positive and negative outcomes at all possible cut offs. MSE: mean square error of the model. PCP: percentage of correct prediction by the model

When validating the overall model in each clinic separately, the model overestimated (Surgery, Urology, Oncology, Gastroenterology, clinics) and underestimated (Diabetic and Endocrine clinic) the actual rate of missed hospital appointments compared to the individual clinic models. For example, the actual rate of missed appointment in the Urology clinic validation dataset was 27.9% and the mean predicted rate of missed appointment using the overall model was 32.6%. In contrast, the actual rate of missed appointments for Diabetic and Endocrine clinic was 25.4% while the mean predicted rate of missed appointment was 16.2% (Table 3).

Table 3: Actual and predicted probability of missed hospital appointment by the overall model stratified by clinic †

Clinic Δ	Actual probability	Predicted probability
Diabetic & Endocrine	25.4 %	16.2 %
Surgery	22.8 %	26.2 %
Urology	27.9 %	32.6 %
Oncology	13.6 %	14.3 %
Gastroenterology	26.9 %	27.4 %

†The general model includes all clinics except Paediatric and Obstetrics & Gynaecology clinic.
Δ Clinics with the highest missed hospital appointment rate and number of scheduled appointments.

3.3 Overbooking simulation

The simulation results (Table 4) show that applying systematic overbooking in the Urology clinic (with high rate of missed appointment) resulted in considerable underuse of available appointments (e.g., average underuse across the 1000 iterations of 13.3% with a systematic overbooking percentage of 20%). However, the Oncology clinic (with lowest rate of missed appointments), underuse was limited to only the 5% and 10% systematic overbooking approaches. The 20% overbooking strategy resulted in a mean percentage of available appointments after overbooking of 0% (95 percentile: -6.9, 8.8) in the Obstetrics clinic. In comparison, the prediction modelling strategy for the Obstetrics clinic resulted in 2.9% (95 percentile: -3.9, 10.8) of appointments still available after overbooking. Supplementary Figure 1 shows the visualization of the simulation results.

Table 4: The differences between attended appointments and daily available appointments after applying each overbooking approach expressed as a percentage of average daily available appointments stratified by clinics, based on 1000 iterations

Overbooking approaches	Diabetic & Endocrine (N=73)	Surgery (N=58)	Urology (N=45)	Oncology (N=48)	Gastroenterology (N=24)	Paediatric (N=137)	Obstetrics & Gynaecology (N=102)
	Mean Percentage (%) and distribution interval (2.5% - 97.5% percentile)						
5%	20.5 (11.0, 31.5)	19.0 (8.6, 31.0)	24.4 (11.1, 37.8)	10.4 (0.0, 20.8)	20.8 (8.3, 41.7)	16.1 (10.2, 23.4)	12.7 (5.9, 20.6)
10%	17.8 (8.2, 28.8)	15.5 (5.2, 27.6)	22.2 (8.9, 35.6)	4.2 (-4.2, 14.6)	20.8 (4.2, 41.7)	11.7 (5.8, 19.0)	7.8 (1.0, 15.7)
15%	13.7 (4.1, 24.7)	10.3 (0.0, 24.1)	17.8 (4.4, 31.1)	0.0 (-8.3, 10.4)	12.5 (-4.2, 33.3)	8.0 (1.5, 15.3)	4.9 (-2.9, 12.7)
20%	9.6 (0.0, 20.5)	6.9 (-5.2, 20.7)	13.3 (0.0, 26.7)	-4.2 (-14.6, 6.3)	12.5 (-8.3, 33.3)	4.4 (-2.2, 11.7)	0.0 (-6.9, 8.8)
25%	6.8 (-2.7, 19.2)	5.2 (-6.9, 17.2)	11.1 (-2.3, 24.4)	-8.3 (-18.8, 4.2)	8.3 (-12.5, 29.2)	0.0 (-6.6, 8.8)	-4.9 (-12.7, 2.9)
30%	2.7 (-8.2, 13.7)	0.0 (-10.3, 13.8)	6.7 (-8.9, 22.2)	-12.5 (-22.9, 0.0)	4.2 (-12.5, 25.0)	-3.6 (-10.9, 4.4)	-8.8 (-16.7, 0.0)
35%	-1.4 (-13.7, 9.6)	-3.4 (-15.5, 10.3)	2.2 (-11.1, 17.8)	-16.7 (-27.1, -6.3)	0.0 (-16.7, 20.8)	-8.0 (-15.3, 0.0)	-12.7 (-20.6, -3.9)
40%	-5.5 (-15.1, 6.8)	-6.9 (-19.0, 6.9)	0.0 (-15.6, 15.6)	-20.8 (-31.3, -8.3)	-4.2 (-25.0, 20.8)	-12.4 (-19.7, -2.9)	-16.7 (-25.5, -7.8)
Prediction Model	5.5 (-4.1, 17.8)	5.2 (-5.2, 17.2)	6.7 (-4.4, 22.2)	2.1 (-6.3, 10.4)	8.3 (-12.5, 25.0)	3.6 (-2.2, 10.9)	2.9 (-3.9, 10.8)

The difference is presented as percentage to compare between clinics.
N: Number of daily available appointments. For the prediction model, the mean predicted risk for each sample was calculated and used to sample the additional observations for each iteration.

In addition, over the 1000 iterations, the prediction modelling approach resulted in fewer iterations where the differences between the attended appointments and the daily available appointments were positive (i.e., clinic underutilised) or zero (i.e., attended appointments were equal to available appointments) and less negative (i.e., clinic overburden) in most of the 1000 iterations when using the prediction model approach compared to the systematic overbooking approaches across all clinics. For example, out of the 1000 iterations, the 30% overbooking in Urology clinic showed that the clinic would be underutilised in 732 iterations, the number of attended appointments would be equal to the daily available appointment in 98 iterations and that the overbooking would cause clinic overburden in 170 iterations if applied. However, applying the prediction model showed that running 836 iterations out of the 1000 iterations would show positive number, with 71 iterations where the daily available appointment were equal to attended appointments and 93 iterations where the clinic would be overburden with extra patients if the prediction model was used to overbook. See supplementary Table 4 & 5 for more details.

4. Discussion

This study developed and validated clinical prediction models for missed hospital appointments in seven outpatient clinics at The Royal Hospital and one overall prediction model including all outpatient clinics (Obstetrics and Gyanecology and Paediatric clinics excluded from the overall prediction model). We found that the developed risk prediction models had good overall discrimination and calibration and the individual clinic models had increased predictive performance than the general model. We also demonstrate the potential use of the developed model to aid in planning for appointment booking. We found that an overbooking strategy based on the clinic-specific risk prediction models resulted, on average, in less clinic overburden than strategies based on fixed overbooking rates (as currently used in the hospital). However; when we take into account the confidence interval and number of iterations that experienced clinical overburden, some systematic overbooking techniques performed 'better' on average than the overbooking approach based on prediction model. This is a difficult decision to choose which approach to implement and that further work undertaking economic evaluation and benefit analysis would be useful.

The development of prediction models to predict missed hospital appointments has been widely reported in the literature.[9] Such models have been developed with differences in term

of the predictors included within those models, the size of the dataset used, extent of internal validation (i.e., splitting the dataset into development and validation cohort), the performance measures used to evaluate the models, the algorithms used to predict missed appointments.[25] Our study builds upon existing literature as we used a large sample size driven with detailed patient data and included patients from multiple clinics. Other studies have used simulated datasets while other studies used small dataset when compared to the size of our dataset. [26,27,28] It has been reported that small sample size would affect the prediction model performance and larger sample size would enhance the model performance.[29,30] Predictors of missed hospital appointments used within our models were selected based on their availability in the hospital system as with other studies.[25] However; some published studies did not include age as predictor of missed hospital appointment in their models.[31] Meanwhile some studies used age as continuous or categorical variables.[32,33] Our model applied fractional polynomial transformation for the age variable which has not been found in any published paper regarding predicting missed hospital appointments.[34] The use of such method specially with age variable have shown an improvement in the model performance as stated in some studies.[35,36]

Most studies that develop prediction models for missed hospital appointments were based on data from single clinics.[37,38,39,40] Our paper compared the performance of an overall model applied to all clinics (except Paediatric clinic and Obstetrics and Gynaecology clinic) versus models for specific clinics. As found, the performance of the individual models was better than the overall model. This could possibly be explained by less heterogeneity in the patients when consider each clinic seperatly[41]. Our models performances were comparable with other studies using logistic regression to build their prediction model (AUC of 0.771 in our study compared to AUC of 0.757 and AUC of 0.768 in other studies).[42,43] The performance of prediction models for individual clinics varied but with high AUC and high percentage of correct prediction (PCP). According to studies, high AUC value indicates better results.[44] Similarly, higher PCP by the model indicates better model performance.[45] The variances within the models might be related to the fact that different datasets were used to build those prediction models for individual clinics. Therefore, individual clinic's dataset is unique in term of patients' characteristics (demographic and clinical characteristics), which caused the models to perform different. Studies indicates that different dataset will effect model perfroamce.[46] Additionally, in most of the published studies few performance metrics were used to evaluate their model commonly area under the curve, mean square error and accuracy.[47,48] However; models in our study were evaluated using multiple performance metrics such as calibration-in-

the-large, calibration intercept, percentage of correct prediction and Brier Score. Using different performance matrix to evaluate the models would give more insight about the results and would provide more informative details. [49]

There have been many published studies evaluating the overbooking approach based on prediction models.[50,51,52,53,54,55] The overbooking approach based on prediction model was often more effective than the systematic overbooking approach in providing additional room for extra appointments to be scheduled without adding more pressure to the healthcare facilities.[56] The same results have been observed in our study where overbooking approach based on prediction model was better than systematic overbooking approach. Our paper compared between the two different approaches using the same dataset, which approach is unique when compared to other studies. The simulation process used in our study shows that an overbooking strategy which taking into account the probability of missed hospital appointment for individual patient based on his/her demographic data and previous appointment data would be better than the standard systematic overbooking.[57,58] Our study is considered to be the first to predict missed hospital appointment and to compare between the systematic overbooking and overbooking based on prediction model in the Sultanate of Oman.

5. Strengths

First, we used a large dataset to build our models, which was extracted from the hospital system including real cases. Our dataset was big when compared to other excited models in other studies[59,60], which improved the accuracy of our models. Secondly, our models looked at the heterogeneity of patients within different outpatients' clinics. Specific model was developed for each clinic taking into consideration that patients within each clinic would be different in their illness and their medical requirements. As a result, the effect of missed hospital appointment predictors would be different in each clinic. For example, waiting time or distance to travel might be a strong predictor for missed appointment in one clinic and might not be an effective predictor in another clinics. Finally, our model included varieties of variables/predictors. Those predictors were stated to be the strong determine of hospital appointment status. When compared to other models, it was obvious that the number of variable/predictors used in our model was higher than the number of variables/predictors included in models developed by other published studies.[61,62,63] This helped to develop more sensitive model that would test /evaluate/detect the patients with higher risk of missed appointment accurately.

6. Limitations

The dataset was extracted from one single tertiary hospital. However, there are other similar hospitals in the capital city of Muscat, which provide tertiary level healthcare services. Also, we did not carry external validity of our prediction models by testing these models in different hospitals from other countries. The findings of this study are based on data collected from a tertiary hospital outpatients clinics providing specialised health care. Further studies are necessary to determine whether the results are generalised to other regions or countries. Finally, we split the data into training-and testing dataets but other methods such as such as cross-validation, can be used.[64'65]. Although, other techniques can be preferred as they do not discard of any data for training, here we had a huge dataset and this reduction in sample size was therefore not likely to impact our findings.

7. Conclusion

We used data available within the hospital health information management system to develop prediction model for missed hospital appointment in multiple clinics. The performance of our models was comparable to other studies with good performance. Our study showed that clinic-specific prediction models outperformed the use of overall model to predict missed appointment for all clinics. The simulation showed that proposed overbooking approach based on risk prediction models is more effective than the current systematic overbooking approach used within the hospital.

Statements and Declarations

Authors' Contributions: AA drafted the ethics application, analysed, interpreted the EHR data and drafted the manuscript. DJ oversaw the development of the models, model testing and models results interpretations. VP oversaw the statistical analyses and reviewed the manuscript. TvS reviewed the ethics application, supervised AA and reviewed the manuscript. All authors read and approved the final manuscript.

Competing Interests: The authors declare that they have no competing interests.

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Data availability statement: Data may be obtained from a third party and are not publicly available. The data that support the findings of this study are available from Ministry of Health, Sultanate of Oman, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available.

Ethical Approval Statement: The study was approved by the Study and Research Centre, Ministry of Health, Sultanate of Oman in 2 May 2019 (proposal ID: MoH/CSR/19/10045).

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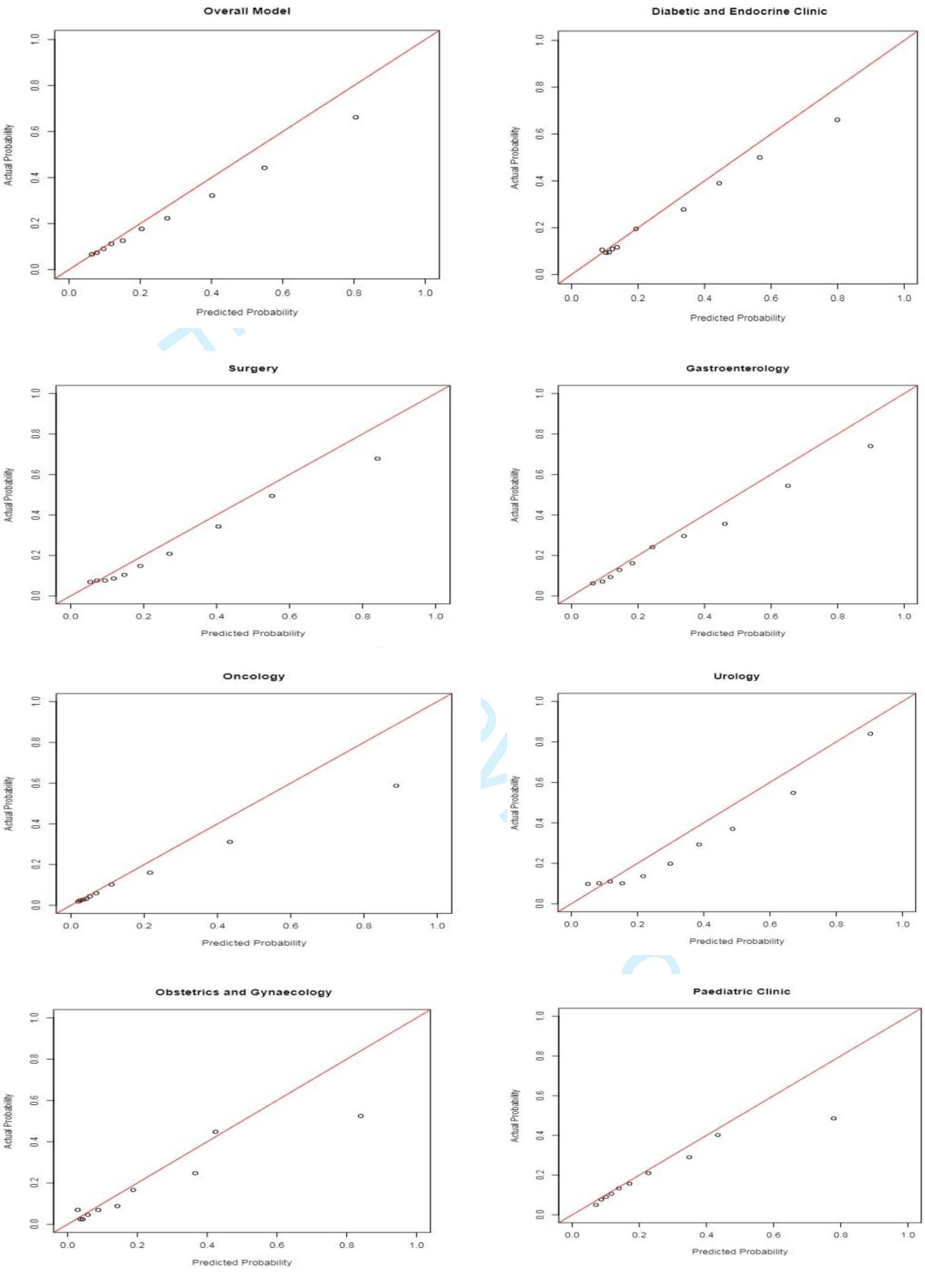
Figure legend:

Figure 1: Calibration curves of the overall model and by clinic
Red line indicates a reference line where predicted and observed probabilities are equal (prefect calibration). Each point indicates the predicted and observed probability of missed hospital appointments in each of the 10 stratum. Point below the reference line indicate over-prediction and above the line indicates under- prediction



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Supplementary Table 1: Development and validation dataset used in the prediction models development by clinic

Model	Development		Validation		Total
	Missed	Attended	Missed	Attended	
Overall model†	105869	354617	26444	88742	575672
Diabetic & Endocrine	21751	65604	5593	16410	109358
Surgery	16262	54559	4032	13635	88488
Urology	12371	31157	3098	7974	54000
Oncology	8158	50749	2023	12815	73745
Gastroenterology	7430	20567	1855	5031	34883
Paediatrics	34646	137299	8562	34218	214725
Obstetrics and Gynaecology	20949	104381	5407	26230	156967

†Includes all clinics except Paediatric clinic and Obstetrics & Gynaecology clinic

Supplementary Table 2: Average daily number of appointments per clinic

Clinic[†]	Number of appointments
Diabetic and Endocrine	73
Surgery	58
Urology	45
Oncology	48
Gastroenterology	24
Paediatric	137
Obstetrics and Gynaecology	102

†Top seven clinics with the highest missed hospital appointment rate and number of scheduled appointments.

Supplementary Table 3: Overall characteristics of the datasets for the top seven clinics.

	Diabetic & Endocrine	Surgery	Urology	Oncology	Gastroenterology	Paediatric	Obstetrics & Gynaecology
	N=109358	N=88488	N= 54600	N=73745	N= 34883	N=214725	N=156967
Appointment Status							
Attended	82014 (74.0)	68194 (77.1)	39131 (71.7)	63564 (86.2)	25598 (73.4)	171517 (79.9)	130611 (83.2)
Missed	27344 (25.0)	20294 (22.9)	15469 (28.3)	10181 (13.8)	9285 (26.6)	43208 (20.1)	26356 (16.8)
Sex							
Female	76872 (70.3)	52915 (59.8)	12240 (22.4)	50022 (67.8)	17410 (49.9)	92820 (43.2)	156967 (100.0)
Male	32486 (29.7)	35573 (40.2)	42360 (77.6)	23723 (32.2)	17473 (50.1)	121905 (56.8)	0 (0.0)
Age (mean (SD))	40.51 (12.77)	45.34 (15.98)	51.47 (17.67)	52.32 (14.96)	42.72 (14.04)	6.49 (5.22)	33.67 (8.28)
Appointment Day							
Sunday	25547 (23.4)	18118 (20.5)	13475 (24.7)	16364 (22.2)	6652 (19.1)	43432 (20.2)	29036 (18.5)
Monday	20995 (19.2)	19084 (21.6)	0 (0.0)	10815 (14.7)	11420 (32.7)	46391 (21.6)	34290 (21.8)
Tuesday	24353 (22.3)	18464 (20.9)	13775 (25.2)	17813 (24.2)	2662 (7.6)	41550 (19.4)	33782 (21.5)
Wednesday	22555 (20.6)	19414 (21.9)	13983 (25.6)	17901 (24.3)	5513 (15.8)	43604 (20.3)	33064 (21.1)
Thursday	15908 (14.5)	13408 (15.2)	13367 (24.5)	10852 (14.7)	8636 (24.8)	39748 (18.5)	26795 (17.1)
Appointment Month							
January	10182 (9.3)	8624 (9.7)	5398 (9.9)	7356 (10.0)	3692 (10.6)	21533 (10.0)	15272 (9.7)
February	9305 (8.5)	8119 (9.2)	4943 (9.1)	6711 (9.1)	3460 (9.9)	20605 (9.6)	15036 (9.6)
March	9900 (9.1)	7812 (8.8)	5037 (9.2)	6509 (8.8)	3307 (9.5)	18369 (8.6)	14663 (9.3)
April	9798 (9.0)	7412 (8.4)	4749 (8.7)	6258 (8.5)	3030 (8.7)	18086 (8.4)	13239 (8.4)
May	9866 (9.0)	7748 (8.8)	4758 (8.7)	6411 (8.7)	3214 (9.2)	18325 (8.5)	13763 (8.8)
June	7440 (6.8)	6347 (7.2)	3963 (7.3)	5346 (7.2)	2501 (7.2)	14699 (6.8)	11366 (7.2)
July	8650 (7.9)	6130 (6.9)	3963 (7.3)	5491 (7.4)	2372 (6.8)	15303 (7.1)	10543 (6.7)
August	7846 (7.2)	6725 (7.6)	4405 (8.1)	6048 (8.2)	2618 (7.5)	15316 (7.1)	10913 (7.0)
September	8290 (7.6)	6776 (7.7)	4043 (7.4)	5605 (7.6)	2859 (8.2)	17131 (8.0)	12240 (7.8)
October	9851 (9.0)	7865 (8.9)	4536 (8.3)	6084 (8.3)	2819 (8.1)	19045 (8.9)	13495 (8.6)
November	8785 (8.0)	7116 (8.0)	4291 (7.9)	5618 (7.6)	2364 (6.8)	17392 (8.1)	12978 (8.3)
December	9445 (8.6)	7814 (8.8)	4514 (8.3)	6308 (8.6)	2647 (7.6)	18927 (8.8)	13459 (8.6)

Marital Status							
Child (<13Years Old)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	175840 (81.9)	0 (0.0)
Single	25551 (23.4)	17290 (19.5)	11286 (20.7)	7949 (10.8)	8732 (25.0)	25385 (11.8)	14568 (9.3)
Married	68618 (62.7)	56865 (64.3)	36104 (66.1)	50316 (68.2)	21259 (60.9)	415 (0.2)	133031 (84.8)
Divorced	647 (0.6)	663 (0.7)	241 (0.4)	438 (0.6)	234 (0.7)	20 (0.0)	473 (0.3)
Widow	919 (0.8)	992 (1.1)	260 (0.5)	847 (1.1)	246 (0.7)	0 (0.0)	335 (0.2)
Missing	13623 (12.5)	12678 (14.3)	6709 (12.3)	14195 (19.2)	4412 (12.6)	13065 (6.1)	8560 (5.5)
Governorate							
Muscat	67945 (62.1)	49496 (55.9)	25634 (46.9)	30980 (42.0)	19959 (57.2)	90519 (42.2)	122871 (78.3)
South Batina	665 (0.6)	1430 (1.6)	488 (0.9)	2683 (3.6)	420 (1.2)	4764 (2.2)	615 (0.4)
AL Dhakiliya	618 (0.6)	435 (0.5)	286 (0.5)	692 (0.9)	152 (0.4)	1402 (0.7)	284 (0.2)
North Batina	1484 (1.4)	842 (1.0)	708 (1.3)	1105 (1.5)	439 (1.3)	2841 (1.3)	952 (0.6)
North Sharqiya	8366 (7.7)	6922 (7.8)	5393 (9.9)	7866 (10.7)	2627 (7.5)	24596 (11.5)	5581 (3.6)
South Sharqiya	8633 (7.9)	7520 (8.5)	3750 (6.9)	10412 (14.1)	2682 (7.7)	24188 (11.3)	4536 (2.9)
AL Dhahira	9429 (8.6)	7472 (8.4)	5831 (10.7)	6979 (9.5)	3930 (11.3)	23099 (10.8)	14288 (9.1)
AL Buriami	3687 (3.4)	4856 (5.5)	5676 (10.4)	4211 (5.7)	1422 (4.1)	15407 (7.2)	2760 (1.8)
AL Wusta	5016 (4.6)	5187 (5.9)	3772 (6.9)	3641 (4.9)	1640 (4.7)	14540 (6.8)	2805 (1.8)
Musandam	3281 (3.0)	3761 (4.3)	2682 (4.9)	4797 (6.5)	1452 (4.2)	11799 (5.5)	2120 (1.4)
Dhofar	234 (0.2)	567 (0.6)	369 (0.7)	373 (0.5)	159 (0.5)	1505 (0.7)	150 (0.1)
GCC Countries	0 (0.0)	0 (0.0)	11 (0.0)	6 (0.0)	1 (0.0)	65 (0.0)	5 (0.0)
Service Cost							
Pay visit and registration fees¥	103881 (95.0)	83928 (94.8)	51255 (93.9)	66992 (90.8)	33284 (95.4)	130591 (60.8)	152055 (96.9)
< 2 Years old*	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	68092 (31.7)	0 (0.0)
Pay all medical service fees†	3069 (2.8)	2898 (3.3)	2020 (3.7)	5736 (7.8)	870 (2.5)	5775 (2.7)	4221 (2.7)
Under Social Affair coverage*	2408 (2.2)	1662 (1.9)	1325 (2.4)	1017 (1.4)	729 (2.1)	10267 (4.8)	691 (0.4)
Appointment waiting group							
< 30 Days	63310 (57.9)	36907 (41.7)	16907 (31.0)	36606 (49.6)	6422 (18.4)	53131 (24.7)	85710 (54.6)
> 30 ≤ 60 Days	14582 (13.3)	18908 (21.4)	5742 (10.5)	8314 (11.3)	5327 (15.3)	24570 (11.4)	36865 (23.5)
> 60 ≤ 90 Days	10646 (9.7)	15329 (17.3)	5020 (9.2)	10586 (14.4)	5519 (15.8)	30480 (14.2)	13051 (8.3)
> 90 ≤ 120 Days	9019 (8.2)	5610 (6.3)	5811 (10.6)	7833 (10.6)	4106 (11.8)	25466 (11.9)	7285 (4.6)
> 120 Days	11801 (10.8)	11734 (13.3)	21120 (38.7)	10406 (14.1)	13509 (38.7)	81078 (37.8)	14056 (9.0)
Nationality							
Omani	104604 (95.7)	84106 (95.0)	51768 (94.8)	66842 (90.6)	33541 (96.2)	207783 (96.8)	149034 (94.9)
Non-Omani	4754 (4.3)	4382 (5.0)	2832 (5.2)	6908 (9.4)	1342 (3.8)	6942 (3.2)	7933 (5.1)

Prior visit group							
Zero prior appointment	9670 (8.8)	20892 (23.6)	17949 (32.9)	5728 (7.8)	7302 (20.9)	52185 (24.3)	36673 (23.4)
One prior appointment	8736 (8.0)	14884 (16.8)	11051 (20.2)	5420 (7.3)	5361 (15.4)	33041 (15.4)	26375 (16.8)
Two prior appointments	7466 (6.8)	10851 (12.3)	6645 (12.2)	4934 (6.7)	3892 (11.2)	22372 (10.4)	19194 (12.2)
Three prior appointments	6479 (5.9)	8051 (9.1)	4411 (8.1)	4573 (6.2)	2963 (8.5)	16483 (7.7)	14544 (9.3)
Four prior appointments	5716 (5.2)	6085 (6.9)	3082 (5.6)	4325 (5.9)	2398 (6.9)	12749 (5.9)	11334 (7.2)
Five prior appointments	5044 (4.6)	4697 (5.3)	2242 (4.1)	4018 (5.4)	1887 (5.4)	10224 (4.8)	8884 (5.7)
> Five prior appointments	66247 (60.6)	23028 (26.0)	9220 (16.9)	44747 (60.7)	11080 (31.8)	67671 (31.5)	39963 (25.5)

¥ Omani citizens, GCC citizens, Expatriate works for government. Expatriate married to Omani. * Exempted from visit and registration fees. †Expatriates pay all medical fees (service fees, visit fees, registration fees).

Supplementary Table 4: Overbooking approaches simulation outcomes for the difference between attended appointments and daily available appointments based on the 1000 iterations by clinic

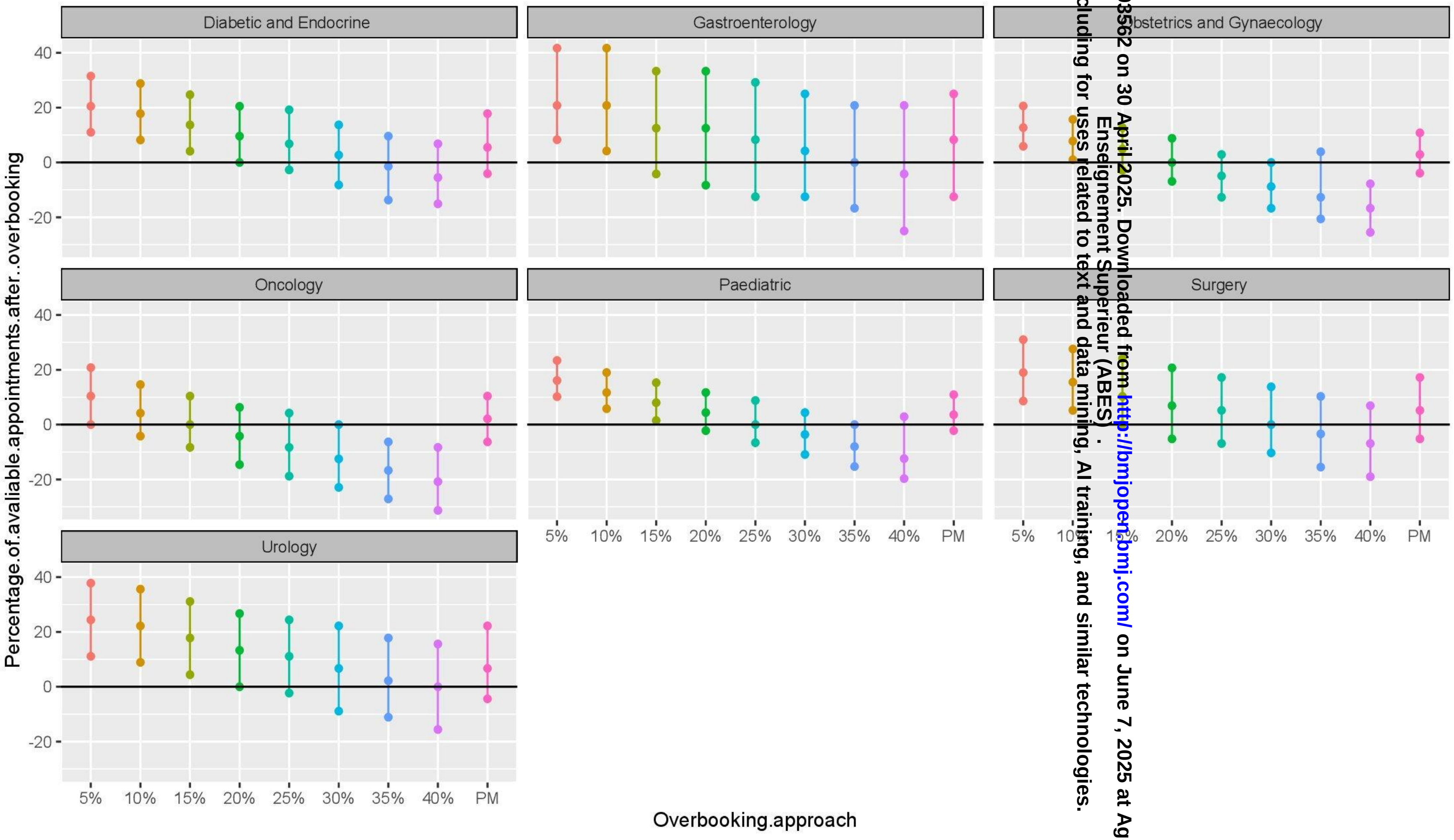
Clinic	Diabetic and Endocrine			Surgery			Urology			Oncology		
Overbooking approach	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero	Positive
5 %	0	0	1000	0	0	1000	0	0	1000	9	19	972
10 %	0	0	1000	2	0	998	1	0	999	133	116	751
15%	2	2	996	9	21	970	4	8	988	367	141	492
20%	20	24	956	84	56	860	17	26	957	734	115	151
25%	84	61	855	188	81	731	53	46	901	891	50	59
30%	297	100	603	401	113	486	170	98	732	966	17	17
35%	577	92	331	652	94	254	292	104	604	997	2	1
40%	763	72	165	840	60	100	451	115	434	1000	0	0
Prediction Model	104	47	849	133	75	792	93	71	836	290	170	540
Clinic	Gastroenterology			Paediatric			Obstetrics and Gynaecology					
Overbooking approach	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero	Positive			
5 %	2	3	995	0	0	1000	0	0	1000			
10 %	4	15	981	0	0	1000	9	6	985			
15%	46	62	892	9	4	987	104	57	839			
20%	99	88	813	93	36	871	422	110	468			
25%	146	154	700	428	74	498	840	59	101			
30%	246	174	580	803	59	138	962	13	25			
35%	383	149	468	973	6	21	996	2	1			
40%	581	149	270	996	2	2	1000	0	0			
Prediction Model	171	138	691	93	47	860	182	80	738			

Negative: proportion of iterations when attended appointments exceed daily available appointments (clinic overburden). Zero: proportion of iterations when attended appointment equal to daily available appointment (all appointments are taken). Positive: proportion of iterations when daily available appointments exceed attended appointments (clinic underutilized)(Extra appointments can be scheduled)

Supplementary Table 5: Distribution analysis of the difference between attended appointments and daily available appointments based on the 1000 iterations for different overbooking approaches by clinic

Clinic	Diabetic & Endocrine				Surgery				Urology				Oncology			
Overbooking approach	Min	Mean	Max	Variance	Min	Mean	Max	Variance	Min	Mean	Max	Variance	Min	Mean	Max	Variance
5 %	5	15	27	13	1	11	23	11	1	11	22	10	-2	5	13	6
10 %	2	13	25	14	-3	9	20	11	-1	10	20	1[illegible]	-5	2	13	6
15%	-2	10	23	14	-3	7	21	12	-4	8	18	1[illegible]	-6	0	9	7
20%	-5	7	19	15	-7	4	16	13	-3	6	18	1[illegible]	-9	-2	8	7
25%	-5	5	20	17	-9	3	15	13	-6	5	16	1[illegible]	-11	-3	6	7
30%	-9	2	14	17	-12	0	13	14	-8	3	16	1[illegible]	-13	-5	3	7
35%	-12	-1	13	18	-14	-1	12	14	-8	1	14	1[illegible]	-16	-8	1	7
40%	-17	-3	13	18	-17	-4	10	14	-11	0	11	1[illegible]	-18	-9	-1	8
Prediction Model	-6	5	19	16	-6	3	14	11	-7	4	15	10	-6	1	7	5
Overbooking approach	Gastroenterology				Paediatric				Obstetrics and Gynaecology							
	Min	Mean	Max	Variance	Min	Mean	Max	Variance	Min	Mean	Max	Variance				
5 %	-1	6	14	5	9	22	36	22	2	13	30	15				
10 %	-2	5	13	5	3	16	32	24	-1	9	25	16				
15%	-4	3	12	6	-2	11	26	24	-6	5	19	16				
20%	-4	3	12	6	-8	6	22	25	-13	0	19	17				
25%	-6	2	12	6	-12	1	17	27	-17	-4	13	16				
30%	-5	1	9	6	-19	-5	11	28	-23	-8	7	15				
35%	-7	0	8	6	-25	-10	7	29	-24	-12	8	2[illegible]				
40%	-9	-1	7	7	-32	-16	3	32	-29	-17	-2	26				
Prediction Model	-5	2	10	5	-7	6	21	22	-7	3	19	14				

Negative: proportion of iterations when attended appointments exceed daily available appointments (clinic overburden). Zero: proportion of iterations when attended appointment equal to daily available appointment (all appointments are taken). Positive: proportion of iterations when daily available appointments exceed attended appointments (clinic underutilized)(Extra appointments can be scheduled)



Supplementray Figure 1 : Feasability of different overbooking approaches by clinic

PM: Prediction Model

BMJ Open

Development and evaluation of prediction models to improve the hospital appointments overbooking strategy at a large tertiary care hospital in Sultanate of Oman

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Development and evaluation of prediction models to improve the hospital appointments overbooking strategy at a large tertiary care hospital in Sultanate of Oman: A Retrospective Analysis

Abstract

Objective: Missed hospital appointments are common among outpatients and have significant clinical and economic consequences. The purpose of this study is to develop a predictive model of missed hospital appointments and to evaluate different overbooking strategies.

Study Design: Retrospective cross-sectional analysis.

Setting: Outpatient clinics of the Royal Hospital in Muscat, Oman.

Participants: All outpatient clinic appointments scheduled between January 2014 and February 2021. (n=947,364).

Primary and secondary outcome measures: Predictive models were created using logistic regression for the entire cohort and individual practices to predict missed hospital appointments. The performance of the models was evaluated using a holdout set. Simulations were performed to compare the effectiveness of predictive model-based overbooking and organizational overbooking in optimizing appointment utilization.

Results: Of the 947,364 outpatient appointments booked, 201,877 (21.3%) were missed. The proportion of missed appointments varied by clinic, ranging from 13.8% in oncology to 28.3% in urology. The AUC for the overall predictive model was 0.771 (95% CI: 0.768-0.775), while the AUC for the clinic-specific predictive model was 0.845 (95% CI: 0.836-0.855) for oncology and 0.738 (95% CI: 0.732-0.744) for pediatrics. The overbooking strategy based on the predictive model outperformed systematic overbooking, with shortages of available appointments at 10.4% in oncology and 25.0% in gastroenterology.

Conclusions: Predictive models can effectively estimate the probability of missing a hospital appointment with high accuracy. Using these models to guide overbooking strategies can enable better appointment scheduling without burdening clinics and reduce the impact of missed appointments.

Keywords: Hospital appointments, Prediction model, Overbooking, Simulation.

Strengths and Limitations of This Study

- This is one of the first studies to develop prediction models specifically for missed hospital appointments.
- This study used a large dataset collected retrospectively, providing robust data for model development.
- The methodology integrated a diverse set of variables to improve prediction accuracy.
- The results were based on data from a single hospital, which may limit the generalizability of the findings.
- The overbooking strategy evaluated in this study reflects real-world scenarios but lacks experimental validation.

1. Background

One of the global challenges in any healthcare system is hospital appointment nonattendance. The rate of missed appointment varies around the world, ranging between 14.9% (Europe) and 27.1% (North America)[1,2], and across healthcare settings. Missed hospital appointments affect the ability of the healthcare facility to provide a good service, leading to patient dissatisfaction; increased waiting times and therefore increased morbidity and mortality.[3] In the UK, £216 million is the estimated annual cost as a result of one million missed GP appointments every month.[4] With rising costs and increasing demands of health care systems, there is a need to utilize available recourses to provide quality care to all patients.[5,6]

Clinical prediction models (CPMs) can be used to predict people at risk of developing certain diseases, predicting disease prognosis and adverse outcomes.[7] They have shown a positive impact in reducing cost, assisting in better decision making for patient heath, allocation of resources and effective utilisation of medical services.[8] Prediction models have been used widely to identify patients with higher risk of missing their hospital appointments. A systematic review including 50 articles showed an increase in the use of such models in the last 10 years by 82% across a range of healthcare settings.[9]

Prediction models are used in UK hospitals to guide appointment strategies and it has been reported that the NHS could save millions using such models.[10,11] Several prediction models for missed appointments have been developed with Area under the receiver operating characteristic curve (AUC) ranging from 0.60 to 0.86.[12,13] These studies use data from a single hospital clinic and were conducted in developed countries [14,15]

Missed hospital appointments are also a major concern for the Royal hospital, Sultanate of Oman, which has an extremely high percentage of missed appointments (22.3% overall and up to 30.3% in Urology clinic). Hence, there is need to implement interventions to reduce the impact of the problem.[16] To our knowledge, no study has developed a prediction model for missed hospital appointments in Oman, but there is opportunity to do so as electronic health record data are available. In this study we aimed to: 1) develop and validate prediction models for missed hospital appointments using the routinely collected data within the patient's electronic medical records

(EMR); and illustrate, through a simulation, the use of the developed prediction models in managing overbooking and compare to systematic overbooking approach being used within the hospital currently.

2. Methods

2.1 Data

Appointment data were extracted from the hospital health information management (ALSHIFA) system, a patient electronic medical record system[17]. All scheduled outpatients appointments were extracted between January 2014 and February 2021 from The Royal Hospital, the largest tertiary referral hospital in the capital city of Muscat, Sultanate of Oman. The data did not include cancelled appointments or rescheduled appointments and walk-in appointments made within the emergency department. From the complete dataset, we split the data by clinics as follows: One overall dataset including all clinics except the Paediatric and Obstetrics clinics due to distinct populations; one dataset for Paediatric clinic; one dataset for the Obstetrics and Gynaecology clinic; and a dataset for each of the remaining five clinics in the overall dataset (Surgery, Urology, Oncology, Gastroenterology, and Diabetic and Endocrine clinic).We applied the data cleaning process as previously described by Alawadhi et al.[18,16]

2.2 Statistical analysis

2.2.1 Risk prediction model

Logistic regression models were developed to predict the risk of missed hospital appointments in each dataset separately. For each clinic specific dataset, patients were randomly divided into a development and validation cohort (80% and 20%, respectively). The development and validation cohorts for Diabetic and Endocrine, Surgery, Urology, Oncology and Gastroenterology clinics were combined to generate the development and validation cohorts for the overall model, respectively. This was to ensure that all models were developed and validated on the same data, such that the development data from each clinic was also used as development data for the individual clinics. Development data were used to fit the model and each developed model was validated in its associated validation data.

Based on our previous work, models were adjusted for the most influential factors for missed appointments, including information on gender, appointment day and month, marital status, governorate (place of residence), appointment waiting time, nationality, and service cost (patient contribution to medical service based on age, nationality and monthly income). For Example, in our previous work, the adjusted OR for missed appointment for Male patient was 1.08 (95% CI 1.06 to 1.10), for appointment day Thursday (adjusted OR 0.84 (95% CI 0.83 to 0.86), for appointment month June was 1.24 (95% CI 1.20 to 1.29), and for waiting time more than 120 days, the adjusted OR was 1.87 (95% CI 1.84 to 1.91). Since this study builds upon our previous findings, our primary focus here is on developing and internally validating each prediction model and then comparing their use for overbooking with systematic overbooking.[16] Appointments were categorised as attended if the patient's visit was created and logged in the system and missing otherwise. All variables were considered linear except age, where fractional polynomials were used.[19]

Performance of the models were evaluated by computing the area under the receiver operating characteristic curve (AUC), mean squared error, percentage of correct prediction (PCP), calibration slope and calibration intercept (calibration-in-the-large).[20,21 22,23 24] Calibration curves were also produced.

2.2.2 Simulating different overbooking approaches for appointment scheduling

Following model development and validation, a simulation study was performed to compare a range of overbooking approaches that could be used in clinical practice and investigate if there is possible added value of using prediction models in overbooking strategies. First, the average number of daily appointments was calculated for each clinic specific dataset (Supplementary Table 2), and this was used to define the number of available daily appointments. Then a random sample of data for each clinic was extracted based on this average and a systematic overbooking simulation was performed, overbooking by 5%, 10%, 15%, 20%, 25%, 30%, 35% and 40%. For example, if the average number of daily appointments were 100 and the overbooking approach was 5%, 100 plus 5 patients would be randomly sampled and the true rate of attendance examined. The systematic overbooking approach was compared to an overbooking approach that used the prediction model where patient-specific probabilities were estimated, and the number of missed appointments predicted in each sample were used to determine the overbooking percentage, sampling an additional number of patients from the clinic specific dataset before examining the true attendance rate.

The simulation was performed 1000 times for each clinic specific dataset. Within each iteration, the difference between the number of available and the number of patients who attended, after applying overbooking, was calculated. A positive value indicated that the number of available appointments exceeded attended appointments (clinic underutilised); a negative value indicated that the number of attended appointments exceeded the number of available appointments (clinic overburdened) and zero indicated that the attended appointments were equal to available appointments. The difference between attended appointments and available appointments was converted to a percentage of appointments available, allowing comparison of approaches across clinics. The mean, median, 2.5% percentile and 97.5% percentile for the difference between attended appointments and available appointments was calculated across the 1000 iterations.

2.2.3 Patient and Public Involvement statement: The study did not require the involvement of patients and the public.

3. Results

3.1 Baseline characteristics of the final dataset used in the study

There were 947,364 appointments in the final dataset, of which 201,877 (21.3%) were missed. The dataset included 576,127 (60.8%) female patients and the mean age was 31 years old (Table 1). The rate of missed appointments was high for patients with waiting times less than 30 days and more than 120 days (17.2%, 26.6%, respectively). Patients with social affair coverage missed 16.8% of their hospital appointment (4229) whereas patients who had to pay their visit and registration fees missed 21.3% of their hospital appointments (175,026). The rate of missed hospital appointments varied across clinics ranging from 13.8% in Oncology to 28.3% in Urology. Supplementary Table 3 shows more details about the characteristics of patients within specific clinics.

Table 1: Characteristics of the complete dataset and stratified by attended and missed appointments

	Overall N (%)	Attended N (%)	Missed N (%)
	947364 (100)	745487 (78.7)	201877 (21.3)
Sex			
Female	576127 (60.8)	459053 (79.7)	117074 (20.3)
Male	371237 (39.2)	286434 (77.2)	84803 (22.8)
Age (mean(SD))	36 (21)	35 (21)	37 (22)
Appointment day			
Sunday	195859 (20.7)	151761 (77.5)	44098 (22.5)
Monday	195169 (20.6)	154070 (78.9)	41099 (21.1)
Tuesday	195560 (20.6)	155172 (79.3)	40388 (20.7)
Wednesday	195784 (20.7)	153109 (78.2)	42675 (21.8)
Thursday	164992 (17.4)	131375 (79.6)	33617 (20.4)
Appointment month			
January	93745 (9.9)	74871 (79.9)	18874 (20.1)
February	88193 (9.3)	71588(81.2)	16605 (18.8)
March	84353 (8.9)	67690 (80.2)	16663 (19.8)
April	80481 (8.5)	63339 (78.7)	17142 (21.3)
May	82685 (8.7)	63726 (77.1)	18959 (22.9)
June	66941 (7.1)	50765 (75.8)	16176 (24.2)
July	67491 (7.1)	52282 (77.5)	15209 (22.5)
August	70167 (7.4)	54240 (77.3)	15927 (22.7)
September	73769 (7.8)	58359 (79.1)	15410 (20.9)
October	82052 (8.7)	64986 (79.2)	17066 (20.8)
November	75444 (8.0)	58908 (78.1)	16536 (21.9)
December	82043 (8.7)	64733 (78.9)	17310 (21.1)
Marital status			
Child (<13Years Old)	175840 (18.6)	141414 (80.4)	34426 (19.6)
Single	150817 (15.9)	116935 (77.5)	33882 (22.5)
Married	509016 (53.7)	403611 (79.3)	105405 (20.7)
Divorced	4270 (0.5)	3264 (76.4)	1006 (23.6)
Widow	6471 (0.7)	4894 (75.6)	1577 (24.4)
Missing	100950 (10.7)	75369 (74.7)	25581 (25.3)
Governorate			
Muscat	516920 (54.6)	402978 (78.0)	113942 (22.0)
South Batina	13884 (1.5)	10469 (75.4)	3415 (24.6)

AL Dhakiliya	5024 (0.5)	3762 (74.9)	1262 (25.1)
North Batina	10762 (1.1)	8094 (75.2)	2668 (24.8)
North Sharqiya	83563 (8.8)	68488 (82.0)	15075 (18.0)
South Sharqiya	84192 (8.9)	67028 (79.6)	17164 (20.4)
AL Dhahira	91251 (9.6)	73226 (80.2)	18025 (19.8)
AL Buriami	50387 (5.3)	38790 (77.0)	11597 (23.0)
AL Wusta	47766 (5.0)	37769 (79.1)	9997 (20.9)
Musandam	39056 (4.1)	31464 (80.6)	7592 (19.4)
Dhofar	4440 (0.5)	3325 (74.9)	1115 (25.1)
GCC Countries	119 (0.0)	94 (79.0)	25 (21.0)
Service cost			
Pay visit and registration fees only¥	822065 (86.8)	647039 (78.7)	175026 (21.3)
<2 Years old*	68092 (7.2)	53542 (78.6)	14550 (21.4)
Pay all medical service fees†	31978 (3.4)	23906 (74.8)	8072 (25.2)
Under Social Affair coverage*	25229 (2.7)	21000 (83.2)	4229 (16.8)
Appointment waiting group			
< 30 Days	365400 (38.6)	302386 (82.8)	63014 (17.2)
> 30 ≤ 60 Days	143100 (15.1)	112852 (78.9)	30248 (21.1)
> 60 ≤ 90 Days	122282 (12.9)	95433 (78.0)	26849 (22.0)
> 90 ≤ 120 Days	91011 (9.6)	69352 (76.2)	21659 (23.8)
> 120 Days	225571 (23.8)	165464 (73.4)	60107 (26.6)
Nationality			
Omani	901263 (95.1)	710802 (78.9)	190461 (21.1)
Non-Omani	46101 (4.9)	34685 (75.2)	11416 (24.8)
Prior visit group			
Zero prior appointment	196293 (20.7)	98469 (50.2)	97824 (49.8)
One prior appointment	135590 (14.3)	99596 (73.5)	35994 (26.5)
Two prior appointments	97431 (10.3)	79616 (81.7)	17815 (18.3)
Three prior appointments	74281 (7.8)	63841 (85.9)	10440 (14.1)
Four prior appointments	58872 (6.2)	52181 (88.6)	6691 (11.4)
Five prior appointments	47752 (5.0)	43039 (90.1)	4713 (9.9)
> Five prior appointments	337145 (35.6)	308745 (91.6)	28400 (8.4)

The distribution for characteristics is displayed vertically for overall observations and horizontally for stratification by attended and missed hospital appointments.

¥ Omani citizens, GCC citizens, Expatriate works for government. Expatriate married to Omani.

* Exempted from visit and registration fees.

†Expatriates pay all medical fees (service fees, visit fees, registration fees).

3.2 Prediction model results

The performance of the overall model and models by clinics varied. The AUC of the overall model was 0.771(95% CI: 0.768-0.775). The Oncology and Obstetrics and Gynaecology clinic models had the highest AUCs of 0.845 (95% CI: 0.836-0.855) and 0.805 (95% CI: 0.799-0.812), respectively, where the performance for Paediatrics was slightly lower (AUC 0.738(95% CI: 0.732-0.744)). The number of appointments in the development and validation datasets for the overall model and by clinic is displayed in supplementary table 1.

The calibration curves for all models can be found in Figure 1. The calibration slope and calibration intercept was variable between models for individual clinics. The Surgery clinic calibration slope and intercept were 1.038 (95% CI: 1.001-1.076) and 0.006 (95% CI: -0.032-0.045), respectively, and the Gastroenterology clinic model had slope of 0.987 (95% CI: 0.932-1.043) and intercept of 0.001(95% CI: -0.060-0.061). The overall model had a calibration slope of 0.994 (95% CI: 0.979-1.009) with calibration intercept of -0.003 (95% CI: -0.018-0.012). See Table 2 for more details.

Table 2: Predictive performance for each model when applied to the validation data

Model	AUC (95% CI)	Accuracy	Calibration slope (95% CI)	Calibration Intercept (95% CI)	MSE	PCP
Overall model†	0.771 (0.768, 0.775)	77.29%	0.994 (0.979, 1.009)	-0.003 (-0.018,0.0[illegible]2)	0.142	0.714
Diabetic & Endocrine	0.764 (0.757, 0.772)	76.91%	0.986 (0.954, 1.019)	0.019 (-0.013, 0.0[illegible]3)	0.153	0.699
Surgery	0.791 (0.783, 0.799)	78.29%	1.038 (1.001, 1.076)	0.006 (-0.034, 0.045)	0.136	0.721
Urology	0.795 (0.785, 0.805)	79.58%	0.973 (0.930, 1.016)	-0.049 (-0.097, -0.001)	0.148	0.698
Oncology	0.845 (0.836, 0.855)	85.24%	0.972 (0.934, 1.012)	-0.009 (-0.064, 0.046)	0.087	0.828
Gastroenterology	0.790 (0.778, 0.802)	79.32%	0.987 (0.932, 1.043)	0.001 (-0.060, 0.061)	0.151	0.702
Paediatric	0.738 (0.732, 0.744)	73.89%	0.996(0.967, 1.025)	-0.0004 (-0.026, 0.025)	0.140	0.719
Obstetrics and Gynaecology	0.805 (0.799, 0.812)	81.08%	0.971(0.942, 0.999)	0.017 (-0.016, 0.050)	0.111	0.780

†Includes all clinics except Paediatric clinic and Obstetrics & Gynaecology clinic. AUC: Area under the ROC curve: an aggregated metric that evaluate how well a logistic regression model classifies positive and negative outcomes at all possible cut offs. MSE: mean square error of the model. PCP: percentage of correct prediction by the model

When validating the overall model in each clinic separately, the model overestimated (Surgery, Urology, Oncology, Gastroenterology, clinics) and underestimated (Diabetic and Endocrine clinic) the actual rate of missed hospital appointments compared to the individual clinic models. For example, the actual rate of missed appointment in the Urology clinic validation dataset was 27.9% and the mean predicted rate of missed appointment using the overall model was 32.6%. In contrast, the actual rate of missed appointments for Diabetic and Endocrine clinic was 25.4% while the mean predicted rate of missed appointment was 16.2% (Table 3).

Table 3: Actual and predicted probability of missed hospital appointment by the overall model stratified by clinic †

Clinic Δ	Actual probability	Predicted probability
Diabetic & Endocrine	25.4 %	16.2 %
Surgery	22.8 %	26.2 %
Urology	27.9 %	32.6 %
Oncology	13.6 %	14.3 %
Gastroenterology	26.9 %	27.4 %

†The general model includes all clinics except Paediatric and Obstetrics & Gynaecology clinic.
Δ Clinics with the highest missed hospital appointment rate and number of scheduled appointments.

3.3 Overbooking simulation

The simulation results (Table 4) show that applying systematic overbooking in the Urology clinic (with high rate of missed appointment) resulted in considerable underuse of available appointments (e.g., average underuse across the 1000 iterations of 13.3% with a systematic overbooking percentage of 20%). However, the Oncology clinic (with lowest rate of missed appointments), underuse was limited to only the 5% and 10% systematic overbooking approaches. The 20% overbooking strategy resulted in a mean percentage of available appointments after overbooking of 0% (95 percentile: -6.9, 8.8) in the Obstetrics clinic. In comparison, the prediction modelling strategy for the Obstetrics clinic resulted in 2.9% (95 percentile: -3.9, 10.8) of appointments still available after overbooking. Supplementary Figure 1 shows the visualization of the simulation results.

Table 4: The differences between attended appointments and daily available appointments after applying each overbooking approach expressed as a percentage of average daily available appointments stratified by clinics, based on 1000 iterations

Overbooking approaches	Diabetic & Endocrine (N=73)	Surgery (N=58)	Urology (N=45)	Oncology (N=48)	Gastroenterology (N=24)	Paediatric (N=137)	Obstetrics & Gynaecology (N=102)
	Mean Percentage (%) and distribution interval (2.5% - 97.5% percentile)						
5%	20.5 (11.0, 31.5)	19.0 (8.6, 31.0)	24.4 (11.1, 37.8)	10.4 (0.0, 20.8)	20.8 (8.3, 41.7)	16.1 (10.2, 23.4)	12.7 (5.9, 20.6)
10%	17.8 (8.2, 28.8)	15.5 (5.2, 27.6)	22.2 (8.9, 35.6)	4.2 (-4.2, 14.6)	20.8 (4.2, 41.7)	11.7 (5.8, 19.0)	7.8 (1.0, 15.7)
15%	13.7 (4.1, 24.7)	10.3 (0.0, 24.1)	17.8 (4.4, 31.1)	0.0 (-8.3, 10.4)	12.5 (-4.2, 33.3)	8.0 (1.5, 15.3)	4.9 (-2.9, 12.7)
20%	9.6 (0.0, 20.5)	6.9 (-5.2, 20.7)	13.3 (0.0, 26.7)	-4.2 (-14.6, 6.3)	12.5 (-8.3, 33.3)	4.4 (-2.2, 11.7)	0.0 (-6.9, 8.8)
25%	6.8 (-2.7, 19.2)	5.2 (-6.9, 17.2)	11.1 (-2.3, 24.4)	-8.3 (-18.8, 4.2)	8.3 (-12.5, 29.2)	0.0 (-6.6, 8.8)	-4.9 (-12.7, 2.9)
30%	2.7 (-8.2, 13.7)	0.0 (-10.3, 13.8)	6.7 (-8.9, 22.2)	-12.5 (-22.9, 0.0)	4.2 (-12.5, 25.0)	-3.6 (-10.9, 4.4)	-8.8 (-16.7, 0.0)
35%	-1.4 (-13.7, 9.6)	-3.4 (-15.5, 10.3)	2.2 (-11.1, 17.8)	-16.7 (-27.1, -6.3)	0.0 (-16.7, 20.8)	-8.0 (-15.3, 0.0)	-12.7 (-20.6, -3.9)
40%	-5.5 (-15.1, 6.8)	-6.9 (-19.0, 6.9)	0.0 (-15.6, 15.6)	-20.8 (-31.3, -8.3)	-4.2 (-25.0, 20.8)	-12.4 (-19.7, -2.9)	-16.7 (-25.5, -7.8)
Prediction Model	5.5 (-4.1, 17.8)	5.2 (-5.2, 17.2)	6.7 (-4.4, 22.2)	2.1 (-6.3, 10.4)	8.3 (-12.5, 25.0)	3.6 (-2.2, 10.9)	2.9 (-3.9, 10.8)

The difference is presented as percentage to compare between clinics.
N: Number of daily available appointments. For the prediction model, the mean predicted risk for each sample was calculated and used to sample the additional observations for each iteration.

In addition, over the 1000 iterations, the prediction modelling approach resulted in fewer iterations where the differences between the attended appointments and the daily available appointments were positive (i.e., clinic underutilised) or zero (i.e., attended appointments were equal to available appointments) and less negative (i.e., clinic overburden) in most of the 1000 iterations when using the prediction model approach compared to the systematic overbooking approaches across all clinics. For example, out of the 1000 iterations, the 30% overbooking in Urology clinic showed that the clinic would be underutilised in 732 iterations, the number of attended appointments would be equal to the daily available appointment in 98 iterations and that the overbooking would cause clinic overburden in 170 iterations if applied. However, applying the prediction model showed that running 836 iterations out of the 1000 iterations would show positive number, with 71 iterations where the daily available appointment were equal to attended appointments and 93 iterations where the clinic would be overburden with extra patients if the prediction model was used to overbook. See supplementary Table 4 & 5 for more details.

4. Discussion

This study developed and validated clinical prediction models for missed hospital appointments in seven outpatient clinics at The Royal Hospital and one overall prediction model including all outpatient clinics (Obstetrics and Gyanecology and Paediatric clinics excluded from the overall prediction model). We found that the developed risk prediction models had good overall discrimination and calibration and the individual clinic models had increased predictive performance than the general model. We also demonstrate the potential use of the developed model to aid in planning for appointment booking. We found that an overbooking strategy based on the clinic-specific risk prediction models resulted, on average, in less clinic overburden than strategies based on fixed overbooking rates (as currently used in the hospital). However; when we take into account the confidence interval and number of iterations that experienced clinical overburden, some systematic overbooking techniques performed 'better' on average than the overbooking approach based on prediction model. This is a difficult decision to choose which approach to implement and that further work undertaking economic evaluation and benefit analysis would be useful.

The development of prediction models to predict missed hospital appointments has been widely reported in the literature.[9] Such models have been developed with differences in term

of the predictors included within those models, the size of the dataset used, extent of internal validation (i.e., splitting the dataset into development and validation cohort), the performance measures used to evaluate the models, the algorithms used to predict missed appointments.[25] Our study builds upon existing literature as we used a large sample size driven with detailed patient data and included patients from multiple clinics. Other studies have used simulated datasets while other studies used small dataset when compared to the size of our dataset. [26,27,28] It has been reported that small sample size would affect the prediction model performance and larger sample size would enhance the model performance.[29,30] Predictors of missed hospital appointments used within our models were selected based on their availability in the hospital system as with other studies.[25] However; some published studies did not include age as predictor of missed hospital appointment in their models.[31] Meanwhile some studies used age as continuous or categorical variables.[32,33] Our model applied fractional polynomial transformation for the age variable which has not been found in any published paper regarding predicting missed hospital appointments.[34] The use of such method especially with age variable has shown an improvement in the model performance as stated in some studies.[35,36]

Most studies that develop prediction models for missed hospital appointments were based on data from single clinics.[37,38,39,40] Our paper compared the performance of an overall model applied to all clinics (except Paediatric clinic and Obstetrics and Gynaecology clinic) versus models for specific clinics. As found, the performance of the individual models was better than the overall model. This could possibly be explained by less heterogeneity in the patients when consider each clinic seperatly[41]. Our models' performance was comparable with other studies using logistic regression to build their prediction model (AUC of 0.771 in our study compared to AUC of 0.757 and AUC of 0.768 in other studies).[42,43] The performance of prediction models for individual clinics varied, showing high AUC and high percentage of correct prediction (PCP). According to studies, high AUC value indicates better results.[44] Similarly, higher PCP by the model indicates better model performance.[45] The variances within the models might be related to the fact that different datasets were used to build those prediction models for individual clinics. Therefore, individual clinic's dataset is unique in term of patients' characteristics (demographic and clinical characteristics), which caused the models to perform different. Studies indicates that different dataset will effect model perfroamce.[46] Additionally, in most of the published studies few performance metrics were used to evaluate their model commonly area under the curve, mean square error and accuracy.[47,48] However; models in our study were evaluated using multiple performance metrics such as calibration-in-

the-large, calibration intercept, percentage of correct prediction and Brier Score. Using different performance matrix to evaluate the models would give more insight about the results and would provide more informative details. [49]

There have been many published studies evaluating the overbooking approach based on prediction models.[50,51,52,53,54,55] The overbooking approach based on prediction models was often more effective than the systematic overbooking approach in providing additional room for extra appointments to be scheduled without adding more pressure to the healthcare facilities.[56] The same results have been observed in our study where the overbooking approach based on prediction models was better than systematic overbooking approach. Our paper compared between the two different approaches using the same dataset, making our approach unique when compared to other studies. The simulation process used in our study shows that an overbooking strategy which taking into account the probability of missed hospital appointment for individual patient based on his/her demographic data and previous appointment data would be better than the standard systematic overbooking.[57,58] To evaluate the possible best approach to missed appointments, we compared a simple algorithm to a predictive models. Each appointment was evaluated individually and patient attendance was predicted based on historical data. A dynamic "look-back window" was implemented, where each appointment was evaluated and overbooking was determined accordingly. This approach allowed for data-driven scheduling adjustments to optimize clinic capacity while minimizing the impact of no-shows**.** Our study is considered to be the first to predict missed hospital appointment and to compare between the systematic overbooking and overbooking based on prediction model in the Sultanate of Oman.

5. Strengths

First, we used a large dataset to build our models, which was extracted from the hospital system including real cases. Our dataset was big when compared to other excited models in other studies[59,60], which improved the accuracy of our models. Secondly, our models looked at the heterogeneity of patients within different outpatients' clinics. Specific model was developed for each clinic taking into consideration that patients within each clinic would be different in their illness and their medical requirements. As a result, the effect of missed hospital appointment predictors would be different in each clinic. For example, waiting time or distance to travel might be a strong predictor for missed appointment in one clinic and might not be an effective predictor in another clinics. Finally, our model included varieties of variables/predictors. Those predictors were stated to be the strong determine of hospital appointment status. When compared to other models, it was obvious that the number of variable/predictors used in our model was higher than the number of variables/predictors included in models developed by other published studies.[61,62,63] This helped to develop more sensitive model that would test /evaluate/detect the patients with higher risk of missed appointment accurately.

6. Limitations

The dataset was extracted from one single tertiary hospital. However, there are other similar hospitals in the capital city of Muscat, which provide tertiary level healthcare services. Also, we did not carry external validity of our prediction models by testing these models in different hospitals from other countries. The findings of this study are based on data collected from a tertiary hospital outpatients clinics providing specialised health care. Further studies are necessary to determine whether the results are generalised to other regions or countries. However, this work has highlighted the importance of developing clinic-specific risk prediction models and the better performance of risk prediction approaches to simple algorithms. Finally, we split the data into training-and testing datasets but other methods such as such as cross-validation, can be used.[64,65]. Although, other techniques can be preferred as they do not discard of any data for training, here we had a huge dataset and this reduction in sample size was therefore not likely to impact our findings.

7. Conclusion

We used data available within the hospital health information management system to develop prediction model for missed hospital appointment in multiple clinics. The performance of our models was comparable to other studies with good performance. Our study showed that clinic-specific prediction models outperformed the use of overall model to predict missed appointment for all clinics. The simulation showed that proposed overbooking approach based on risk prediction models is more effective than the current systematic overbooking approach used within the hospital.

Statements and Declarations

Authors' Contributions: AA drafted the ethics application, analysed, interpreted the EHR data and drafted the manuscript. DJ oversaw the development of the models, model testing and models results interpretations. VP oversaw the statistical analyses and reviewed the manuscript. TvS reviewed the ethics application, supervised AA and reviewed the manuscript. All authors read and approved the final manuscript. AA is the guarantor of this work and takes full responsibility for the accuracy of the data and the integrity of the research.

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Data availability statement: Data may be obtained from a third party and are not publicly available. The data that support the findings of this study are available from Ministry of Health, Sultanate of Oman, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available.

Ethical Statement: The study was approved by the Study and Research Centre, Ministry of Health, Sultanate of Oman in 2 May 2019 (proposal ID: MoH/CSR/19/10045). Data were anonymised prior to being accessed by the study authors

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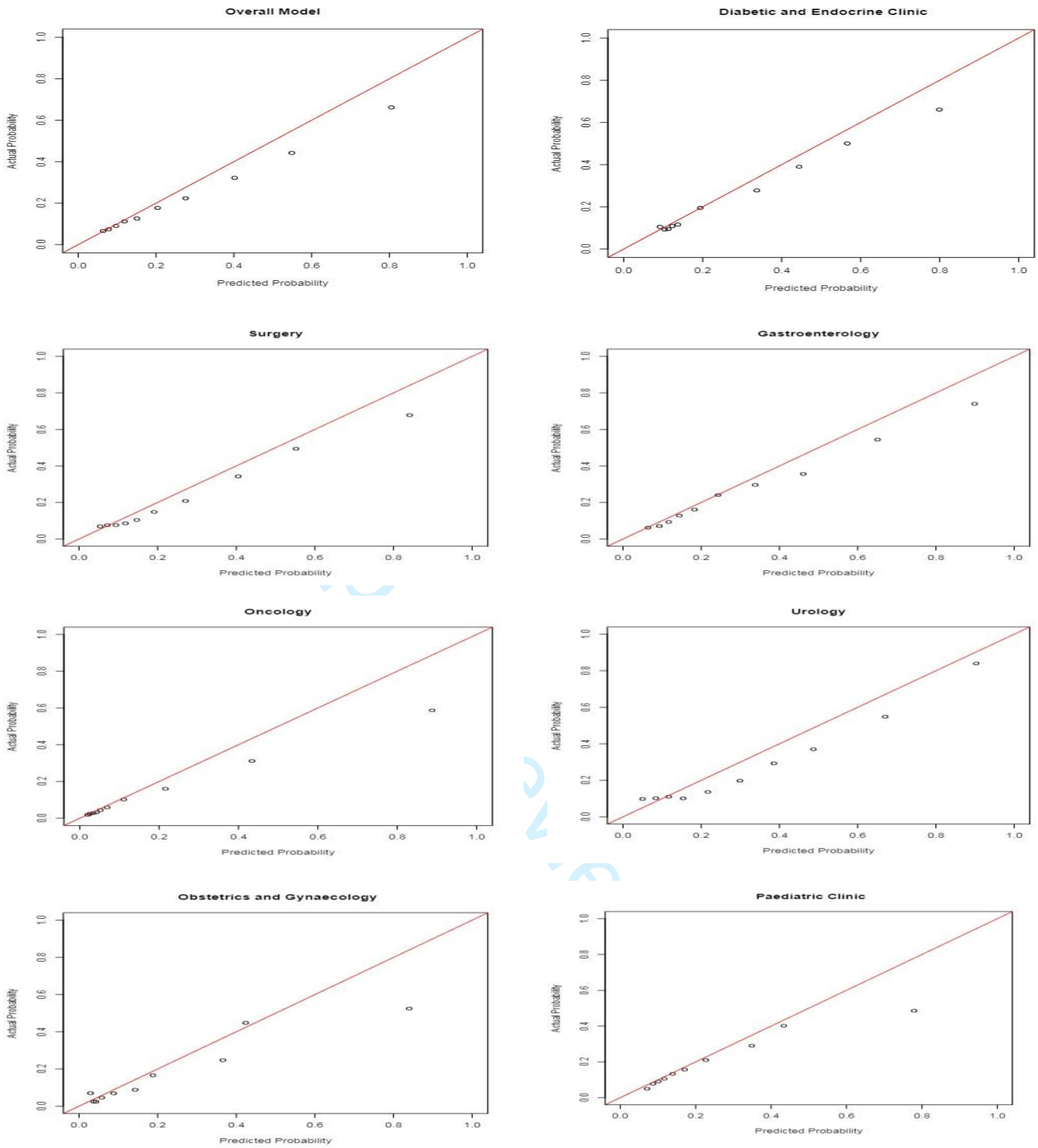
Figure legend:

Figure 1: Calibration curves of the overall model and by clinic
Red line indicates a reference line where predicted and observed probabilities are equal (prefect calibration). Each point indicates the predicted and observed probability of missed hospital appointments in each of the 10 stratum. Point below the reference line indicate over-prediction and above the line indicates under- prediction



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Red line indicates a reference line where predicted and observed probabilities are equal (prefect calibration). Each point indicates the predicted and observed probability of missed hospital appointments in each of the 10 stratum. Point below the reference line indicate over-prediction and above the line indicates under- prediction.

Supplementary Table 1: Development and validation dataset used in the prediction models development by clinic

Model	Development		Validation		Total
	Missed	Attended	Missed	Attended	
Overall model†	105869	354617	26444	88742	575672
Diabetic & Endocrine	21751	65604	5593	16410	109358
Surgery	16262	54559	4032	13635	88488
Urology	12371	31157	3098	7974	54000
Oncology	8158	50749	2023	12815	73745
Gastroenterology	7430	20567	1855	5031	34883
Paediatrics	34646	137299	8562	34218	214725
Obstetrics and Gynaecology	20949	104381	5407	26230	156967

†Includes all clinics except Paediatric clinic and Obstetrics & Gynaecology clinic

Supplementary Table 2: Average daily number of appointments per clinic

Clinic†	Number of appointments
Diabetic and Endocrine	73
Surgery	58
Urology	45
Oncology	48
Gastroenterology	24
Paediatric	137
Obstetrics and Gynaecology	102

†Top seven clinics with the highest missed hospital appointment rate and number of scheduled appointments.

Supplementary Table 3: Overall characteristics of the datasets for the top seven clinics.

	Diabetic & Endocrine	Surgery	Urology	Oncology	Gastroenterology	Paediatric	Obstetrics & Gynaecology
	N=109358	N=88488	N= 54600	N=73745	N= 34883	N=214725	N=156967
Appointment Status							
Attended	82014 (74.0)	68194 (77.1)	39131 (71.7)	63564 (86.2)	25598 (73.4)	171517 (79.9)	130611 (83.2)
Missed	27344 (25.0)	20294 (22.9)	15469 (28.3)	10181 (13.8)	9285 (26.6)	43208 (20.1)	26356 (16.8)
Sex							
Female	76872 (70.3)	52915 (59.8)	12240 (22.4)	50022 (67.8)	17410 (49.9)	92820 (43.2)	156967 (100.0)
Male	32486 (29.7)	35573 (40.2)	42360 (77.6)	23723 (32.2)	17473 (50.1)	121905 (56.8)	0 (0.0)
Age (mean (SD))	40.51 (12.77)	45.34 (15.98)	51.47 (17.67)	52.32 (14.96)	42.72 (14.[illegible]4)	6.49 (5.22)	33.67 (8.28)
Appointment Day							
Sunday	25547 (23.4)	18118 (20.5)	13475 (24.7)	16364 (22.2)	6652 (19.1)	43432 (20.2)	29036 (18.5)
Monday	20995 (19.2)	19084 (21.6)	0 (0.0)	10815 (14.7)	11420 (32.7)	46391 (21.6)	34290 (21.8)
Tuesday	24353 (22.3)	18464 (20.9)	13775 (25.2)	17813 (24.2)	2662 (7.6)	41550 (19.4)	33782 (21.5)
Wednesday	22555 (20.6)	19414 (21.9)	13983 (25.6)	17901 (24.3)	5513 (15.8)	43604 (20.3)	33064 (21.1)
Thursday	15908 (14.5)	13408 (15.2)	13367 (24.5)	10852 (14.7)	8636 (24.8)	39748 (18.5)	26795 (17.1)
Appointment Month							
January	10182 (9.3)	8624 (9.7)	5398 (9.9)	7356 (10.0)	3692 (10.6)	21533 (10.0)	15272 (9.7)
February	9305 (8.5)	8119 (9.2)	4943 (9.1)	6711 (9.1)	3460 (9.9)	20605 (9.6)	15036 (9.6)
March	9900 (9.1)	7812 (8.8)	5037 (9.2)	6509 (8.8)	3307 (9.5)	18369 (8.6)	14663 (9.3)
April	9798 (9.0)	7412 (8.4)	4749 (8.7)	6258 (8.5)	3030 (8.7)	18086 (8.4)	13239 (8.4)
May	9866 (9.0)	7748 (8.8)	4758 (8.7)	6411 (8.7)	3214 (9.2)	18325 (8.5)	13763 (8.8)
June	7440 (6.8)	6347 (7.2)	3963 (7.3)	5346 (7.2)	2501 (7.2)	14699 (6.8)	11366 (7.2)
July	8650 (7.9)	6130 (6.9)	3963 (7.3)	5491 (7.4)	2372 (6.8)	15303 (7.1)	10543 (6.7)
August	7846 (7.2)	6725 (7.6)	4405 (8.1)	6048 (8.2)	2618 (7.5)	15316 (7.1)	10913 (7.0)
September	8290 (7.6)	6776 (7.7)	4043 (7.4)	5605 (7.6)	2859 (8.2)	17131 (8.0)	12240 (7.8)
October	9851 (9.0)	7865 (8.9)	4536 (8.3)	6084 (8.3)	2819 (8.1)	19045 (8.9)	13495 (8.6)
November	8785 (8.0)	7116 (8.0)	4291 (7.9)	5618 (7.6)	2364 (6.8)	17392 (8.1)	12978 (8.3)
December	9445 (8.6)	7814 (8.8)	4514 (8.3)	6308 (8.6)	2647 (7.6)	18927 (8.8)	13459 (8.6)

Marital Status							
Child (<13Years Old)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	175840 (81.9)	0 (0.0)
Single	25551 (23.4)	17290 (19.5)	11286 (20.7)	7949 (10.8)	8732 (25.0)	25385 (11.8)	14568 (9.3)
Married	68618 (62.7)	56865 (64.3)	36104 (66.1)	50316 (68.2)	21259 (60.9)	415 (0.2)	133031 (84.8)
Divorced	647 (0.6)	663 (0.7)	241 (0.4)	438 (0.6)	234 (0.7)	20 (0.0)	473 (0.3)
Widow	919 (0.8)	992 (1.1)	260 (0.5)	847 (1.1)	246 (0.7)	0 (0.0)	335 (0.2)
Missing	13623 (12.5)	12678 (14.3)	6709 (12.3)	14195 (19.2)	4412 (12.6)	13065 (6.1)	8560 (5.5)
Governorate							
Muscat	67945 (62.1)	49496 (55.9)	25634 (46.9)	30980 (42.0)	19959 (57.2)	90519 (42.2)	122871 (78.3)
South Batina	665 (0.6)	1430 (1.6)	488 (0.9)	2683 (3.6)	420 (1.2)	4764 (2.2)	615 (0.4)
AL Dhakiliya	618 (0.6)	435 (0.5)	286 (0.5)	692 (0.9)	152 (0.4)	1402 (0.7)	284 (0.2)
North Batina	1484 (1.4)	842 (1.0)	708 (1.3)	1105 (1.5)	439 (1.3)	2841 (1.3)	952 (0.6)
North Sharqiya	8366 (7.7)	6922 (7.8)	5393 (9.9)	7866 (10.7)	2627 (7.[illegible])	24596 (11.5)	5581 (3.6)
South Sharqiya	8633 (7.9)	7520 (8.5)	3750 (6.9)	10412 (14.1)	2682 (7.[illegible])	24188 (11.3)	4536 (2.9)
AL Dhahira	9429 (8.6)	7472 (8.4)	5831 (10.7)	6979 (9.5)	3930 (11.3)	23099 (10.8)	14288 (9.1)
AL Buriami	3687 (3.4)	4856 (5.5)	5676 (10.4)	4211 (5.7)	1422 (4.1)	15407 (7.2)	2760 (1.8)
AL Wusta	5016 (4.6)	5187 (5.9)	3772 (6.9)	3641 (4.9)	1640 (4.7)	14540 (6.8)	2805 (1.8)
Musandam	3281 (3.0)	3761 (4.3)	2682 (4.9)	4797 (6.5)	1452 (4.2)	11799 (5.5)	2120 (1.4)
Dhofar	234 (0.2)	567 (0.6)	369 (0.7)	373 (0.5)	159 (0.5)	1505 (0.7)	150 (0.1)
GCC Countries	0 (0.0)	0 (0.0)	11 (0.0)	6 (0.0)	1 (0.0)	65 (0.0)	5 (0.0)
Service Cost							
Pay visit and registration fees[¥]	103881 (95.0)	83928 (94.8)	51255 (93.9)	66992 (90.8)	33284 (95.4)	130591 (60.8)	152055 (96.9)
< 2 Years old*	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	68092 (31.7)	0 (0.0)
Pay all medical service fees†	3069 (2.8)	2898 (3.3)	2020 (3.7)	5736 (7.8)	870 (2.5)	5775 (2.7)	4221 (2.7)
Under Social Affair coverage*	2408 (2.2)	1662 (1.9)	1325 (2.4)	1017 (1.4)	729 (2.1)	10267 (4.8)	691 (0.4)
Appointment waiting group							
< 30 Days	63310 (57.9)	36907 (41.7)	16907 (31.0)	36606 (49.6)	6422 (18.4)	53131 (24.7)	85710 (54.6)
> 30 ≤ 60 Days	14582 (13.3)	18908 (21.4)	5742 (10.5)	8314 (11.3)	5327 (15.3)	24570 (11.4)	36865 (23.5)
> 60 ≤ 90 Days	10646 (9.7)	15329 (17.3)	5020 (9.2)	10586 (14.4)	5519 (15.8)	30480 (14.2)	13051 (8.3)
> 90 ≤ 120 Days	9019 (8.2)	5610 (6.3)	5811 (10.6)	7833 (10.6)	4106 (11.8)	25466 (11.9)	7285 (4.6)
> 120 Days	11801 (10.8)	11734 (13.3)	21120 (38.7)	10406 (14.1)	13509 (38.7)	81078 (37.8)	14056 (9.0)
Nationality							
Omani	104604 (95.7)	84106 (95.0)	51768 (94.8)	66842 (90.6)	33541 (96.2)	207783 (96.8)	149034 (94.9)
Non-Omani	4754 (4.3)	4382 (5.0)	2832 (5.2)	6908 (9.4)	1342 (3.8)	6942 (3.2)	7933 (5.1)

Prior visit group							
Zero prior appointment	9670 (8.8)	20892 (23.6)	17949 (32.9)	5728 (7.8)	7302 (20.9)	52185 (24.3)	36673 (23.4)
One prior appointment	8736 (8.0)	14884 (16.8)	11051 (20.2)	5420 (7.3)	5361 (15.4)	33041 (15.4)	26375 (16.8)
Two prior appointments	7466 (6.8)	10851 (12.3)	6645 (12.2)	4934 (6.7)	3892 (11.2)	22372 (10.4)	19194 (12.2)
Three prior appointments	6479 (5.9)	8051 (9.1)	4411 (8.1)	4573 (6.2)	2963 (8.5)	16483 (7.7)	14544 (9.3)
Four prior appointments	5716 (5.2)	6085 (6.9)	3082 (5.6)	4325 (5.9)	2398 (6.9)	12749 (5.9)	11334 (7.2)
Five prior appointments	5044 (4.6)	4697 (5.3)	2242 (4.1)	4018 (5.4)	1887 (5.4)	10224 (4.8)	8884 (5.7)
> Five prior appointments	66247 (60.6)	23028 (26.0)	9220 (16.9)	44747 (60.7)	11080 (31.8)	67671 (31.5)	39963 (25.5)

¥ Omani citizens, GCC citizens, Expatriate works for government. Expatriate married to Omani. * Exempted from visit and registration fees. †Expatriates pay all medical fees (service fees, visit fees, registration fees).

Supplementary Table 4: Overbooking approaches simulation outcomes for the difference between attended appointments and daily available appointments based on the 1000 iterations by clinic

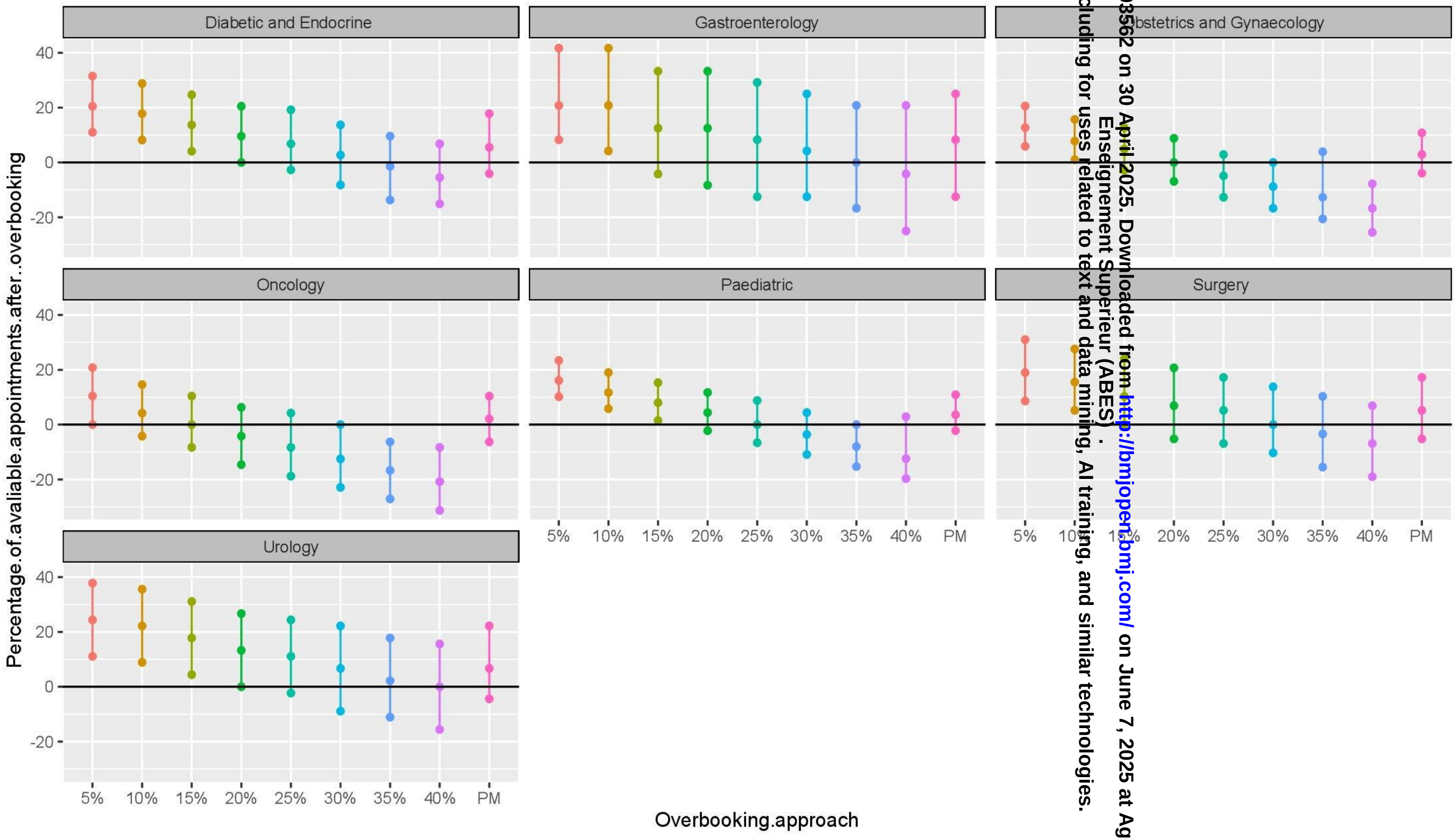
Clinic	Diabetic and Endocrine			Surgery			Urology			Oncology		
Overbooking approach	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero	Positive
5 %	0	0	1000	0	0	1000	0	0	1000	9	19	972
10 %	0	0	1000	2	0	998	1	0	999	133	116	751
15%	2	2	996	9	21	970	4	8	988	367	141	492
20%	20	24	956	84	56	860	17	26	957	734	115	151
25%	84	61	855	188	81	731	53	46	901	891	50	59
30%	297	100	603	401	113	486	170	98	732	966	17	17
35%	577	92	331	652	94	254	292	104	604	997	2	1
40%	763	72	165	840	60	100	451	115	434	1000	0	0
Prediction Model	104	47	849	133	75	792	93	71	836	290	170	540
Clinic	Gastroenterology			Paediatric			Obstetrics and Gynaecology					
Overbooking approach	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero	Positive			
5 %	2	3	995	0	0	1000	0	0	1000			
10 %	4	15	981	0	0	1000	9	6	985			
15%	46	62	892	9	4	987	104	57	839			
20%	99	88	813	93	36	871	422	110	468			
25%	146	154	700	428	74	498	840	59	101			
30%	246	174	580	803	59	138	962	13	25			
35%	383	149	468	973	6	21	996	2	1			
40%	581	149	270	996	2	2	1000	0	0			
Prediction Model	171	138	691	93	47	860	182	80	738			

Negative: proportion of iterations when attended appointments exceed daily available appointments (clinic overburden). Zero: proportion of iterations when attended appointment equal to daily available appointment (all appointments are taken). Positive: proportion of iterations when daily available appointments exceed attended appointments (clinic underutilized)(Extra appointments can be scheduled)

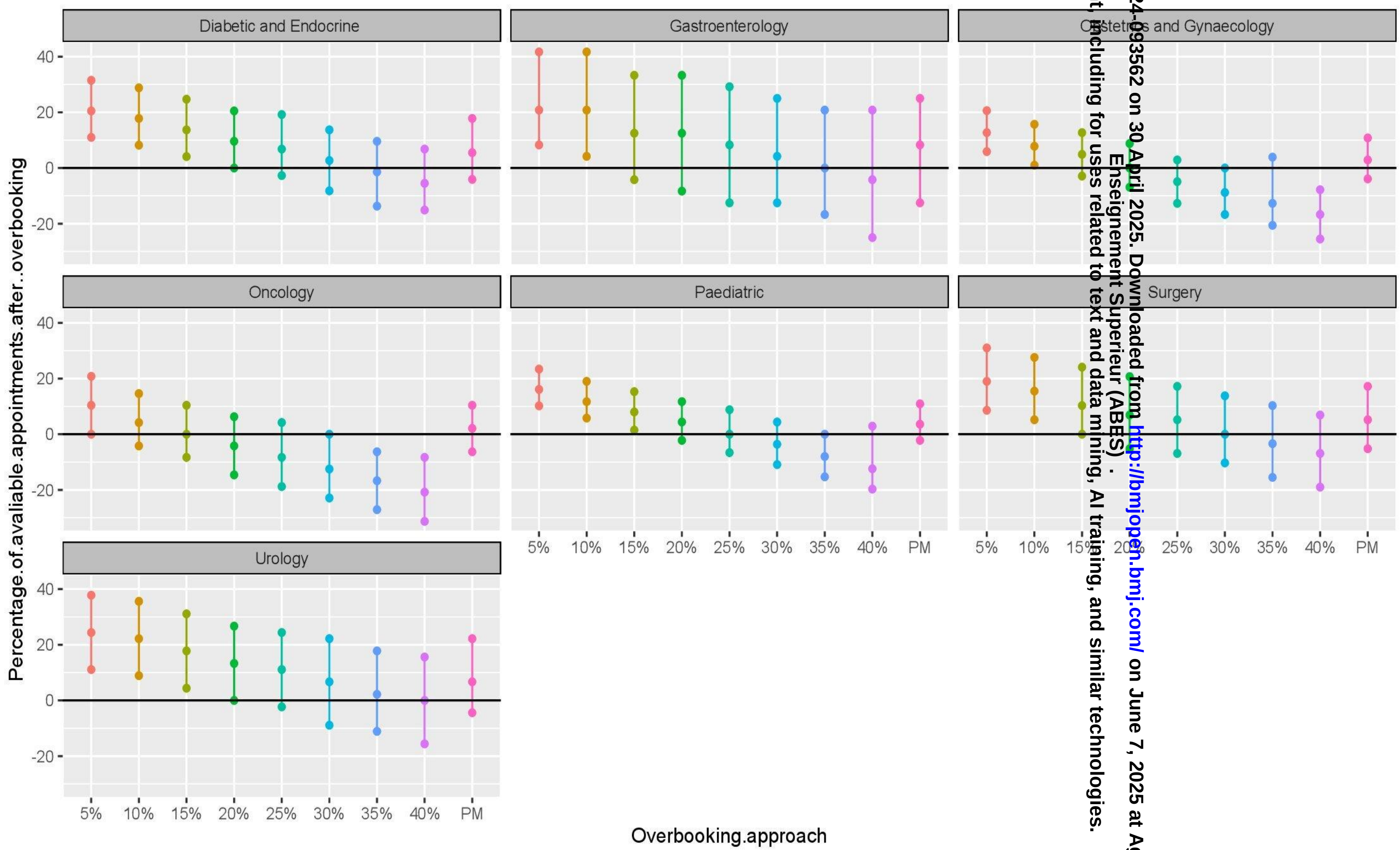
Supplementary Table 5: Distribution analysis of the difference between attended appointments and daily available appointments based on the 1000 iterations for different overbooking approaches by clinic

Clinic	Diabetic & Endocrine				Surgery				Urology				Oncology			
Overbooking approach	Min	Mean	Max	Variance	Min	Mean	Max	Variance	Min	Mean	Max	Variance	Min	Mean	Max	Variance
5 %	5	15	27	13	1	11	23	11	1	11	22	10	-2	5	13	6
10 %	2	13	25	14	-3	9	20	11	-1	10	20	1[illegible]	-5	2	13	6
15%	-2	10	23	14	-3	7	21	12	-4	8	18	1[illegible]	-6	0	9	7
20%	-5	7	19	15	-7	4	16	13	-3	6	18	1[illegible]	-9	-2	8	7
25%	-5	5	20	17	-9	3	15	13	-6	5	16	1[illegible]	-11	-3	6	7
30%	-9	2	14	17	-12	0	13	14	-8	3	16	1[illegible]	-13	-5	3	7
35%	-12	-1	13	18	-14	-1	12	14	-8	1	14	1[illegible]	-16	-8	1	7
40%	-17	-3	13	18	-17	-4	10	14	-11	0	11	1[illegible]	-18	-9	-1	8
Prediction Model	-6	5	19	16	-6	3	14	11	-7	4	15	1[illegible]	-6	1	7	5
Overbooking approach	Gastroenterology				Paediatric				Obstetrics and Gynaecology							
	Min	Mean	Max	Variance	Min	Mean	Max	Variance	Min	Mean	Max	Variance				
5 %	-1	6	14	5	9	22	36	22	2	13	30	15				
10 %	-2	5	13	5	3	16	32	24	-1	9	25	16				
15%	-4	3	12	6	-2	11	26	24	-6	5	19	16				
20%	-4	3	12	6	-8	6	22	25	-13	0	19	17				
25%	-6	2	12	6	-12	1	17	27	-17	-4	13	16				
30%	-5	1	9	6	-19	-5	11	28	-23	-8	7	19				
35%	-7	0	8	6	-25	-10	7	29	-24	-12	8	2[illegible]				
40%	-9	-1	7	7	-32	-16	3	32	-29	-17	-2	26				
Prediction Model	-5	2	10	5	-7	6	21	22	-7	3	19	14				

Negative: proportion of iterations when attended appointments exceed daily available appointments (clinic overburden). Zero: proportion of iterations when attended appointment equal to daily available appointment (all appointments are taken). Positive: proportion of iterations when daily available appointments exceed attended appointments (clinic underutilized)(Extra appointments can be scheduled)



Supplementray Figure 1 : Feasability of different overbooking approaches by clinic
PM: Prediction Model



Supplementray Figure 1 : Feasability of different overbooking approaches by clinic
PM: Prediction Model

BMJ Open

Development and evaluation of prediction models to improve the hospital appointments overbooking strategy at a large tertiary care hospital in Sultanate of Oman

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Development and evaluation of prediction models to improve the hospital appointments overbooking strategy at a large tertiary care hospital in Sultanate of Oman: A Retrospective Analysis

Abstract

Objective: Missed hospital appointments are common among outpatients and have significant clinical and economic consequences. The purpose of this study is to develop a predictive model of missed hospital appointments and to evaluate different overbooking strategies.

Study Design: Retrospective cross-sectional analysis.

Setting: Outpatient clinics of the Royal Hospital in Muscat, Oman.

Participants: All outpatient clinic appointments scheduled between January 2014 and February 2021. (n=947,364).

Primary and secondary outcome measures: Predictive models were created using logistic regression for the entire cohort and individual practices to predict missed hospital appointments. The performance of the models was evaluated using a holdout set. Simulations were performed to compare the effectiveness of predictive model-based overbooking and organisational overbooking in optimizing appointment utilisation.

Results: Of the 947,364 outpatient appointments booked, 201,877 (21.3%) were missed. The proportion of missed appointments varied by clinic, ranging from 13.8% in oncology to 28.3% in urology. The AUC for the overall predictive model was 0.771 (95% CI: 0.768-0.775), while the AUC for the clinic-specific predictive model was 0.845 (95% CI: 0.836-0.855) for oncology and 0.738 (95% CI: 0.732-0.744) for pediatrics. The overbooking strategy based on the predictive model outperformed systematic overbooking, with shortages of available appointments at 10.4% in oncology and 25.0% in gastroenterology.

Conclusions: Predictive models can effectively estimate the probability of missing a hospital appointment with high accuracy. Using these models to guide overbooking strategies can enable better appointment scheduling without burdening clinics and reduce the impact of missed appointments.

Keywords: Hospital appointments, Prediction model, Overbooking, Simulation.

Strengths and Limitations of This Study

- This study used a large hospital dataset, providing robust data for development of model to predict missed out-patient hospital appointments.
- The methodology integrated a diverse set of variables to improve prediction accuracy.
- The results were based on data from a single hospital, which may limit the generalisability of the findings.
- The overbooking strategy evaluated in this study reflects real-world scenarios but lacks experimental validation.

1. Background

One of the global challenges in any healthcare system is hospital appointment nonattendance. The rate of missed appointment varies around the world, ranging between 14.9% (Europe) and 27.1% (North America)[1,2], and across healthcare settings. Missed hospital appointments affect the ability of the healthcare facility to provide a good service, leading to patient dissatisfaction; increased waiting times and therefore increased morbidity and mortality.[3] In the UK, £216 million is the estimated annual cost as a result of one million missed GP appointments every month.[4] With rising costs and increasing demands of health care systems, there is a need to utilise available recourses to provide quality care to all patients.[5,6]

Clinical prediction models (CPMs) can be used to predict people at risk of developing certain diseases, predicting disease prognosis and adverse outcomes.[7] They have shown a positive impact in reducing cost, assisting in better decision making for patient heath, allocation of resources and effective utilisation of medical services.[8] Prediction models have been used widely to identify patients with higher risk of missing their hospital appointments. A systematic review including 50 articles showed an increase in the use of such models in the last 10 years by 82% across a range of healthcare settings.[9]

Prediction models are used in UK hospitals to guide appointment strategies and it has been reported that the NHS could save millions using such models.[10,11] Several prediction models for missed appointments have been developed with Area under the receiver operating characteristic curve (AUC) ranging from 0.60 to 0.86.[12,13] These studies use data from a single hospital clinic and were conducted in developed countries [14,15]

Missed hospital appointments are also a major concern for the Royal hospital, Sultanate of Oman, which has an extremely high percentage of missed appointments (22.3% overall and up to 30.3% in Urology clinic). Hence, there is need to implement interventions to reduce the impact of the problem.[16] To our knowledge, no study has developed a prediction model for missed hospital appointments in Oman, but there is opportunity to do so as electronic health record data are available. In this study we aimed to: 1) develop and validate prediction models for missed hospital appointments using the routinely collected data within the patient's electronic medical records

(EMR); and illustrate, through a simulation, the use of the developed prediction models in managing overbooking and compare to systematic overbooking approach being used within the hospital currently.

2. Methods

2.1 Data

Appointment data were extracted from the hospital health information management (ALSHIFA) system, a patient electronic medical record system[17]. All scheduled outpatients appointments were extracted between January 2014 and February 2021 from The Royal Hospital, the largest tertiary referral hospital in the capital city of Muscat, Sultanate of Oman. The data did not include cancelled appointments or rescheduled appointments and walk-in appointments made within the emergency department. From the complete dataset, we split the data by clinics as follows: One overall dataset including all clinics except the Paediatric and Obstetrics clinics due to distinct populations; one dataset for Paediatric clinic; one dataset for the Obstetrics and Gynaecology clinic; and a dataset for each of the remaining five clinics in the overall dataset (Surgery, Urology, Oncology, Gastroenterology, and Diabetic and Endocrine clinic).We applied the data cleaning process as previously described by Alawadhi et al.[18,16]

2.2 Statistical analysis

2.2.1 Risk prediction model

Logistic regression models were developed to predict the risk of missed hospital appointments in each dataset separately. For each clinic specific dataset, patients were randomly divided into a development and validation cohort (80% and 20%, respectively). The development and validation cohorts for Diabetic and Endocrine, Surgery, Urology, Oncology and Gastroenterology clinics were combined to generate the development and validation cohorts for the overall model, respectively. This was to ensure that all models were developed and validated on the same data, such that the development data from each clinic was also used as development data for the individual clinics. Development data were used to fit the model and each developed model was validated in its associated validation data.

Based on our previous work, models were adjusted for the most influential factors for missed appointments, including information on gender, appointment day and month, marital status, governorate (place of residence), appointment waiting time, nationality, and service cost (patient contribution to medical service based on age, nationality and monthly income). For Example, in our previous work, the adjusted OR for missed appointment for Male patient was 1.08 (95% CI 1.06 to 1.10), for appointment day Thursday (adjusted OR 0.84 (95% CI 0.83 to 0.86), for appointment month June was 1.24 (95% CI 1.20 to 1.29), and for waiting time more than 120 days, the adjusted OR was 1.87 (95% CI 1.84 to 1.91). Since this study builds upon our previous findings, our primary focus here is on developing and internally validating each prediction model and then comparing their use for overbooking with systematic overbooking.[16] Appointments were categorised as attended if the patient's visit was created and logged in the system and missing otherwise. All variables were considered linear except age, where fractional polynomials were used.[19]

Performance of the models were evaluated by computing the area under the receiver operating characteristic curve (AUC), mean squared error, percentage of correct prediction (PCP), calibration slope and calibration intercept (calibration-in-the-large).[20,21 22,23 24] Calibration curves were also produced.

2.2.2 Simulating different overbooking approaches for appointment scheduling

After the development and validation of the models, a simulation study was performed to evaluate a range of overbooking approaches that could be used in clinical practice and the possible added value of using prediction models. This simulation study used the following steps. First, the average number of daily appointments was calculated for each clinic specific dataset (Supplementary Table 2) in order, to define the number of available daily appointments. Then a random sample of data for each clinic was extracted based on this average and a systematic overbooking simulation was performed, overbooking by 5%, 10%, 15%, 20%, 25%, 30%, 35% and 40%. For example, if the average number of daily appointments were 100 and the overbooking approach was 5%, 100 plus 5 patients would be randomly sampled and the true rate of attendance examined. The systematic overbooking approach was compared to an overbooking approach that used the prediction model where patient-specific probabilities were estimated, and the number of missed appointments predicted in each sample were used to determine the overbooking percentage, sampling an additional number of patients from the clinic specific dataset before examining the true attendance rate.

The simulation was performed 1000 times for each clinic specific dataset. Within each iteration, the difference between the number of available and the number of patients who attended, after applying overbooking, was calculated. A positive value indicated that the number of available appointments exceeded attended appointments (clinic underutilised); a negative value indicated that the number of attended appointments exceeded the number of available appointments (clinic overburdened) and zero indicated that the attended appointments were equal to available appointments. The difference between attended appointments and available appointments was converted to a percentage of appointments available, allowing comparison of approaches across clinics. For each of the 1,000 iterations, we calculated the mean, median, and the 2.5th and 97.5th percentiles of the difference between the number of attended appointments and the number of available appointments.

3. Results

3.1 Baseline characteristics of the final dataset used in the study

There were 947,364 appointments in the final dataset, of which 201,877 (21.3%) were missed. The dataset included 576,127 (60.8%) female patients and the mean age was 31 years old (Table 1). The rate of missed appointments was high for patients with waiting times less than 30 days and more than 120 days (17.2%, 26.6%, respectively). Patients with social affair coverage missed 16.8% of their hospital appointment (4229) whereas patients who had to pay their visit and registration fees missed 21.3% of their hospital appointments (175,026). The rate of missed hospital appointments varied across clinics ranging from 13.8% in Oncology to 28.3% in Urology. Supplementary Table 3 shows more details about the characteristics of patients within specific clinics.

Table 1: Characteristics of the complete dataset and stratified by attended and missed appointments

	Overall N (%)	Attended N (%)	Missed N (%)
	947364 (100)	745487 (78.7)	201877 (21.3)
Sex			
Female	576127 (60.8)	459053 (79.7)	117074 (20.3)
Male	371237 (39.2)	286434 (77.2)	84803 (22.8)
Age (mean(SD))	36 (21)	35 (21)	37 (22)
Appointment day			
Sunday	195859 (20.7)	151761 (77.5)	44098 (22.5)
Monday	195169 (20.6)	154070 (78.9)	41099 (21.1)
Tuesday	195560 (20.6)	155172 (79.3)	40388 (20.7)
Wednesday	195784 (20.7)	153109 (78.2)	42675 (21.8)
Thursday	164992 (17.4)	131375 (79.6)	33617 (20.4)
Appointment month			
January	93745 (9.9)	74871 (79.9)	18874 (20.1)
February	88193 (9.3)	71588(81.2)	16605 (18.8)
March	84353 (8.9)	67690 (80.2)	16663 (19.8)
April	80481 (8.5)	63339 (78.7)	17142 (21.3)
May	82685 (8.7)	63726 (77.1)	18959 (22.9)
June	66941 (7.1)	50765 (75.8)	16176 (24.2)
July	67491 (7.1)	52282 (77.5)	15209 (22.5)
August	70167 (7.4)	54240 (77.3)	15927 (22.7)
September	73769 (7.8)	58359 (79.1)	15410 (20.9)
October	82052 (8.7)	64986 (79.2)	17066 (20.8)
November	75444 (8.0)	58908 (78.1)	16536 (21.9)
December	82043 (8.7)	64733 (78.9)	17310 (21.1)
Marital status			
Child (<13Years Old)	175840 (18.6)	141414 (80.4)	34426 (19.6)
Single	150817 (15.9)	116935 (77.5)	33882 (22.5)
Married	509016 (53.7)	403611 (79.3)	105405 (20.7)
Divorced	4270 (0.5)	3264 (76.4)	1006 (23.6)
Widow	6471 (0.7)	4894 (75.6)	1577 (24.4)
Missing	100950 (10.7)	75369 (74.7)	25581 (25.3)
Governorate			
Muscat	516920 (54.6)	402978 (78.0)	113942 (22.0)
South Batina	13884 (1.5)	10469 (75.4)	3415 (24.6)
AL Dhakiliya	5024 (0.5)	3762 (74.9)	1262 (25.1)
North Batina	10762 (1.1)	8094 (75.2)	2668 (24.8)
North Sharqiya	83563 (8.8)	68488 (82.0)	15075 (18.0)
South Sharqiya	84192 (8.9)	67028 (79.6)	17164 (20.4)
AL Dhahira	91251 (9.6)	73226 (80.2)	18025 (19.8)
AL Buriami	50387 (5.3)	38790 (77.0)	11597 (23.0)
AL Wusta	47766 (5.0)	37769 (79.1)	9997 (20.9)
Musandam	39056 (4.1)	31464 (80.6)	7592 (19.4)
Dhofar	4440 (0.5)	3325 (74.9)	1115 (25.1)
GCC Countries	119 (0.0)	94 (79.0)	25 (21.0)
Service cost			
Pay visit and registration fees only[¥]	822065 (86.8)	647039 (78.7)	175026 (21.3)
<2 Years old*	68092 (7.2)	53542 (78.6)	14550 (21.4)
Pay all medical service fees[†]	31978 (3.4)	23906 (74.8)	8072 (25.2)
Under Social Affair coverage*	25229 (2.7)	21000 (83.2)	4229 (16.8)
Appointment waiting group			
< 30 Days	365400 (38.6)	302386 (82.8)	63014 (17.2)
> 30 ≤ 60 Days	143100 (15.1)	112852 (78.9)	30248 (21.1)
> 60 ≤ 90 Days	122282 (12.9)	95433 (78.0)	26849 (22.0)
> 90 ≤ 120 Days	91011 (9.6)	69352 (76.2)	21659 (23.8)

> 120 Days	225571 (23.8)	165464 (73.4)	60107 (26.6)
Nationality			
Omani	901263 (95.1)	710802 (78.9)	190461 (21.1)
Non-Omani	46101 (4.9)	34685 (75.2)	11416 (24.8)
Prior visit group			
Zero prior appointment	196293 (20.7)	98469 (50.2)	97824 (49.8)
One prior appointment	135590 (14.3)	99596 (73.5)	35994 (26.5)
Two prior appointments	97431 (10.3)	79616 (81.7)	17815 (18.3)
Three prior appointments	74281 (7.8)	63841 (85.9)	10440 (14.1)
Four prior appointments	58872 (6.2)	52181 (88.6)	6691 (11.4)
Five prior appointments	47752 (5.0)	43039 (90.1)	4713 (9.9)
> Five prior appointments	337145 (35.6)	308745 (91.6)	28400 (8.4)

The distribution for characteristics is displayed vertically for overall observations and horizontally for stratification by attended and missed hospital appointments.

¥ Omani citizens, GCC citizens, Expatriate works for government. Expatriate married to Omani.

* Exempted from visit and registration fees.

†Expatriates pay all medical fees (service fees, visit fees, registration fees).

3.2 Prediction model results

The performance of the overall model and models by clinics varied. The AUC of the overall model was 0.771(95% CI: 0.768-0.775). The Oncology and Obstetrics and Gynaecology clinic models had the highest AUCs of 0.845 (95% CI: 0.836-0.855) and 0.805 (95% CI: 0.799-0.812), respectively, where the performance for Paediatrics was slightly lower (AUC 0.738(95% CI: 0.732-0.744)). The number of appointments in the development and validation datasets for the overall model and by clinic is displayed in supplementary table 1.

The calibration curves for all models can be found in Figure 1. The calibration slope and calibration intercept was variable between models for individual clinics. The Surgery clinic calibration slope and intercept were 1.038 (95% CI: 1.001-1.076) and 0.006 (95% CI: -0.032-0.045), respectively, and the Gastroenterology clinic model had slope of 0.987 (95% CI: 0.932-1.043) and intercept of 0.001(95% CI: -0.060-0.061). The overall model had a calibration slope of 0.994 (95% CI: 0.979-1.009) with calibration intercept of -0.003 (95% CI: -0.018-0.012). See Table 2 for more details.

Table 2: Predictive performance for each model when applied to the validation data

Model	AUC (95% CI)	Accuracy	Calibration slope (95% CI)	Calibration Intercept (95% CI)	MSE	PCP
Overall model†	0.771 (0.768, 0.775)	77.29%	0.994 (0.979, 1.009)	-0.003 (-0.018,0.012)	0.142	0.714
Diabetic & Endocrine	0.764 (0.757, 0.772)	76.91%	0.986 (0.954, 1.019)	0.019 (-0.013, 0.053)	0.153	0.699
Surgery	0.791 (0.783, 0.799)	78.29%	1.038 (1.001, 1.076)	0.006 (-0.034, 0.045)	0.136	0.721
Urology	0.795 (0.785, 0.805)	79.58%	0.973 (0.930, 1.016)	-0.049 (-0.097, -0.001)	0.148	0.698
Oncology	0.845 (0.836, 0.855)	85.24%	0.972 (0.934, 1.012)	-0.009 (-0.064, 0.046)	0.087	0.828
Gastroenterology	0.790 (0.778, 0.802)	79.32%	0.987 (0.932, 1.043)	0.001 (-0.060, 0.061)	0.151	0.702
Paediatric	0.738 (0.732, 0.744)	73.89%	0.996(0.967, 1.025)	-0.0004 (-0.026, 0.025)	0.140	0.719
Obstetrics and Gynaecology	0.805 (0.799, 0.812)	81.08%	0.971(0.942, 0.999)	0.017 (-0.016, 0.050)	0.111	0.780

†Includes all clinics except Paediatric clinic and Obstetrics & Gynaecology clinic. AUC: Area under the ROC curve: an aggregated metric that evaluate how well a logistic regression model classifies positive and negative outcomes at all possible cut offs. MSE: mean square error of the model. PCP: percentage of correct prediction by the model

When validating the overall model in each clinic separately, the model overestimated (Surgery, Urology, Oncology, Gastroenterology, clinics) and underestimated (Diabetic and Endocrine clinic) the actual rate of missed hospital appointments compared to the individual clinic models. For example, the actual rate of missed appointment in the Urology clinic validation dataset was 27.9% and the mean predicted rate of missed appointment using the overall model was 32.6%. In contrast, the actual rate of missed appointments for Diabetic and Endocrine clinic was 25.4% while the mean predicted rate of missed appointment was 16.2% (Table 3).

Table 3: Actual and predicted probability of missed hospital appointment by the overall model stratified by clinic †

Clinic Δ	Actual probability	Predicted probability
Diabetic & Endocrine	25.4 %	16.2 %
Surgery	22.8 %	26.2 %
Urology	27.9 %	32.6 %
Oncology	13.6 %	14.3 %
Gastroenterology	26.9 %	27.4 %

†The general model includes all clinics except Paediatric and Obstetrics & Gynaecology clinic.
Δ Clinics with the highest missed hospital appointment rate and number of scheduled appointments.

3.3 Overbooking simulation

The simulation results (Table 4) show that applying systematic overbooking in the Urology clinic (with high rate of missed appointment) resulted in considerable underuse of available appointments (e.g., average underuse across the 1000 iterations of 13.3% with a systematic overbooking percentage of 20%). However, the Oncology clinic (with lowest rate of missed appointments), underuse was limited to only the 5% and 10% systematic overbooking approaches. The 20% overbooking strategy resulted in a mean percentage of available appointments after overbooking of 0% (95 percentile: -6.9, 8.8) in the Obstetrics clinic. In comparison, the prediction modelling strategy for the Obstetrics clinic resulted in 2.9% (95 percentile: -3.9, 10.8) of appointments still available after overbooking. Supplementary Figure 1 shows the visualisation of the simulation results.

Table 4: The differences between attended appointments and daily available appointments after applying each overbooking approach expressed as a percentage of average daily available appointments stratified by clinics, based on 1000 iterations

Overbooking approaches	Diabetic & Endocrine (N=73)	Surgery (N=58)	Urology (N=45)	Oncology (N=48)	Gastroenterology (N=24)	Paediatric (N=137)	Obstetrics & Gynaecology (N=102)
	Mean Percentage (%) and distribution interval (2.5% - 97.5% percentile)						
5%	20.5 (11.0, 31.5)	19.0 (8.6, 31.0)	24.4 (11.1, 37.8)	10.4 (0.0, 20.8)	20.8 (8.3, 41.7)	16.1 (10.2, 23.4)	12.7 (5.9, 20.6)
10%	17.8 (8.2, 28.8)	15.5 (5.2, 27.6)	22.2 (8.9, 35.6)	4.2 (-4.2, 14.6)	20.8 (4.2, 41.7)	11.7 (5.8, 19.0)	7.8 (1.0, 15.7)
15%	13.7 (4.1, 24.7)	10.3 (0.0, 24.1)	17.8 (4.4, 31.1)	0.0 (-8.3, 10.4)	12.5 (-4.2, 33.3)	8.0 (1.5, 15.3)	4.9 (-2.9, 12.7)
20%	9.6 (0.0, 20.5)	6.9 (-5.2, 20.7)	13.3 (0.0, 26.7)	-4.2 (-14.6, 6.3)	12.5 (-8.3, 33.3)	4.4 (-2.2, 11.7)	0.0 (-6.9, 8.8)
25%	6.8 (-2.7, 19.2)	5.2 (-6.9, 17.2)	11.1 (-2.3, 24.4)	-8.3 (-18.8, 4.2)	8.3 (-12.5, 29.2)	0.0 (-6.6, 8.8)	-4.9 (-12.7, 2.9)
30%	2.7 (-8.2, 13.7)	0.0 (-10.3, 13.8)	6.7 (-8.9, 22.2)	-12.5 (-22.9, 0.0)	4.2 (-12.5, 25.0)	-3.6 (-10.9, 4.4)	-8.8 (-16.7, 0.0)
35%	-1.4 (-13.7, 9.6)	-3.4 (-15.5, 10.3)	2.2 (-11.1, 17.8)	-16.7 (-27.1, -6.3)	0.0 (-16.7, 20.8)	-8.0 (-15.3, 0.0)	-12.7 (-20.6, -3.9)
40%	-5.5 (-15.1, 6.8)	-6.9 (-19.0, 6.9)	0.0 (-15.6, 15.6)	-20.8 (-31.3, -8.3)	-4.2 (-25.0, 20.8)	-12.4 (-19.7, -2.9)	-16.7 (-25.5, -7.8)
Prediction Model	5.5 (-4.1, 17.8)	5.2 (-5.2, 17.2)	6.7 (-4.4, 22.2)	2.1 (-6.3, 10.4)	8.3 (-12.5, 25.0)	3.6 (-2.2, 10.9)	2.9 (-3.9, 10.8)

The difference is presented as percentage to compare between clinics.
N: Number of daily available appointments. For the prediction model, the mean predicted risk for each sample was calculated and used to sample the additional observations for each iteration.

In addition, over the 1000 iterations, the prediction modelling approach resulted in fewer iterations where the differences between the attended appointments and the daily available appointments were positive (i.e., clinic underutilised) or zero (i.e., attended appointments were equal to available appointments) and less negative (i.e., clinic overburden) in most of the 1000 iterations when using the prediction model approach compared to the systematic overbooking approaches across all clinics. For example, out of the 1000 iterations, the 30% overbooking in Urology clinic showed that the clinic would be underutilised in 732 iterations, the number of attended appointments would be equal to the daily available appointment in 98 iterations and that the overbooking would cause clinic overburden in 170 iterations if applied. However, applying the prediction model showed that running 836 iterations out of the 1000 iterations would show positive number, with 71 iterations where the daily available appointment were equal to attended appointments and 93 iterations where the clinic would be overburden with extra patients if the prediction model was used to overbook. See supplementary Table 4 & 5 for more details.

4. Discussion

This study developed and validated clinical prediction models for missed hospital appointments in seven outpatient clinics at The Royal Hospital and one overall prediction model including all outpatient clinics (Obstetrics and Gyanecology and Paediatric clinics excluded from the overall prediction model). We found that the developed risk prediction models had good overall discrimination and calibration and the individual clinic models had increased predictive performance than the general model. We also demonstrate the potential use of the developed model to aid in planning for appointment booking. We found that an overbooking strategy based on the clinic-specific risk prediction models resulted, on average, in less clinic overburden than strategies based on fixed overbooking rates (as currently used in the hospital). However; when we take into account the confidence interval and number of iterations that experienced clinical overburden, some systematic overbooking techniques performed 'better' on average than the overbooking approach based on prediction model. This is a difficult decision to choose which approach to implement and that further work undertaking economic evaluation and benefit analysis would be useful.

The development of prediction models to predict missed hospital appointments has been widely reported in the literature.[9] Such models have been developed with differences in term

of the predictors included within those models, the size of the dataset used, extent of internal validation (i.e., splitting the dataset into development and validation cohort), the performance measures used to evaluate the models, the algorithms used to predict missed appointments.[25] Our study builds upon existing literature as we used a large sample size driven with detailed patient data and included patients from multiple clinics. Other studies have used simulated datasets while other studies used small dataset when compared to the size of our dataset. [26,27,28] It has been reported that small sample size would affect the prediction model performance and larger sample size would enhance the model performance.[29,30] Predictors of missed hospital appointments used within our models were selected based on their availability in the hospital system as with other studies.[25] However; some published studies did not include age as predictor of missed hospital appointment in their models.[31] Meanwhile some studies used age as continuous or categorical variables.[32,33] Our model applied fractional polynomial transformation for the age variable which has not been found in any published paper regarding predicting missed hospital appointments.[34] The use of such method especially with age variable has shown an improvement in the model performance as stated in some studies.[35,36]

Most studies that develop prediction models for missed hospital appointments were based on data from single clinics.[37,38,39,40] Our paper compared the performance of an overall model applied to all clinics (except Paediatric clinic and Obstetrics and Gynaecology clinic) versus models for specific clinics. As found, the performance of the individual models was better than the overall model. This could possibly be explained by less heterogeneity in the patients when consider each clinic seperatly[41]. Our models' performance was comparable with other studies using logistic regression to build their prediction model (AUC of 0.771 in our study compared to AUC of 0.757 and AUC of 0.768 in other studies).[42,43] The performance of prediction models for individual clinics varied, showing high AUC and high percentage of correct prediction (PCP). According to studies, high AUC value indicates better results.[44] Similarly, higher PCP by the model indicates better model performance.[45] The variances within the models might be related to the fact that different datasets were used to build those prediction models for individual clinics. Therefore, individual clinic's dataset is unique in term of patients' characteristics (demographic and clinical characteristics), which caused the models to perform different. Studies indicates that different dataset will effect model perfroamce.[46] Additionally, in most of the published studies few performance metrics were used to evaluate their model commonly area under the curve, mean square error and accuracy.[47,48] However; models in our study were evaluated using multiple performance metrics such as calibration-in-

the-large, calibration intercept, percentage of correct prediction and Brier Score. Using different performance matrix to evaluate the models would give more insight about the results and would provide more informative details. [49]

There have been many published studies evaluating the overbooking approach based on prediction models.[50,51,52,53,54,55] The overbooking approach based on prediction models was often more effective than the systematic overbooking approach in providing additional room for extra appointments to be scheduled without adding more pressure to the healthcare facilities.[56] The same results have been observed in our study where the overbooking approach based on prediction models was better than systematic overbooking approach. Our paper compared between the two different approaches using the same dataset, making our approach unique when compared to other studies. The simulation process used in our study shows that an overbooking strategy which taking into account the probability of missed hospital appointment for individual patient based on his/her demographic data and previous appointment data would be better than the standard systematic overbooking.[57,58] To evaluate the possible best approach to missed appointments, we compared a simple algorithm to a predictive models. Each appointment was evaluated individually and patient attendance was predicted based on historical data. A dynamic "look-back window" was implemented, where each appointment was evaluated and overbooking was determined accordingly. This approach allowed for data-driven scheduling adjustments to optimise clinic capacity while minimizing the impact of no-shows**.** Our study is considered to be the first to predict missed hospital appointment and to compare between the systematic overbooking and overbooking based on prediction model in the Sultanate of Oman.

5. Strengths

First, we used a large dataset to build our models, which was extracted from the hospital system including real cases. Our dataset was big when compared to other excited models in other studies[59,60], which improved the accuracy of our models. Secondly, our models looked at the heterogeneity of patients within different outpatients' clinics. Specific model was developed for each clinic taking into consideration that patients within each clinic would be different in their illness and their medical requirements. As a result, the effect of missed hospital appointment predictors would be different in each clinic. For example, waiting time or distance to travel might be a strong predictor for missed appointment in one clinic and might not be an effective predictor in another clinics. Finally, our model included varieties of variables/predictors. Those predictors were stated to be the strong determine of hospital appointment status. When compared to other models, it was obvious that the number of variable/predictors used in our model was higher than the number of variables/predictors included in models developed by other published studies.[61,62,63] This helped to develop more sensitive model that would test /evaluate/detect the patients with higher risk of missed appointment accurately.

6. Limitations

The dataset was extracted from one single tertiary hospital. However, there are other similar hospitals in the capital city of Muscat, which provide tertiary level healthcare services. Also, we did not carry external validity of our prediction models by testing these models in different hospitals from other countries. The findings of this study are based on data collected from a tertiary hospital outpatients clinics providing specialised health care. Further studies are necessary to determine whether the results are generalised to other regions or countries. However, this work has highlighted the importance of developing clinic-specific risk prediction models and the better performance of risk prediction approaches to simple algorithms. Finally, we split the data into training-and testing datasets but other methods such as such as cross-validation, can be used.[64,65]. Although, other techniques can be preferred as they do not discard of any data for training, here we had a huge dataset and this reduction in sample size was therefore not likely to impact our findings.

7. Conclusion

We used data available within the hospital health information management system to develop prediction model for missed hospital appointment in multiple clinics. The performance of our models was comparable to other studies with good performance. Our study showed that clinic-specific prediction models outperformed the use of overall model to predict missed appointment for all clinics. The simulation showed that proposed overbooking approach based on risk prediction models is more effective than the current systematic overbooking approach used within the hospital.

Statements and Declarations

Authors' Contributions: AA drafted the ethics application, analysed, interpreted the EHR data and drafted the manuscript. DJ oversaw the development of the models, model testing and models results interpretations. VP oversaw the statistical analyses and reviewed the manuscript. TvS reviewed the ethics application, supervised AA and reviewed the manuscript. All authors read and approved the final manuscript. AA is the guarantor of this work and takes full responsibility for the accuracy of the data and the integrity of the research.

Competing Interests: The authors declare that they have no competing interests.

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Data availability statement: Data may be obtained from a third party and are not publicly available. The data that support the findings of this study are available from Ministry of Health, Sultanate of Oman, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available.

Ethical Statement: The study was approved by the Study and Research Centre, Ministry of Health, Sultanate of Oman in 2 May 2019 (proposal ID: MoH/CSR/19/10045). Data were anonymised prior to being accessed by the study authors

Patient and Public Involvement statement: None.

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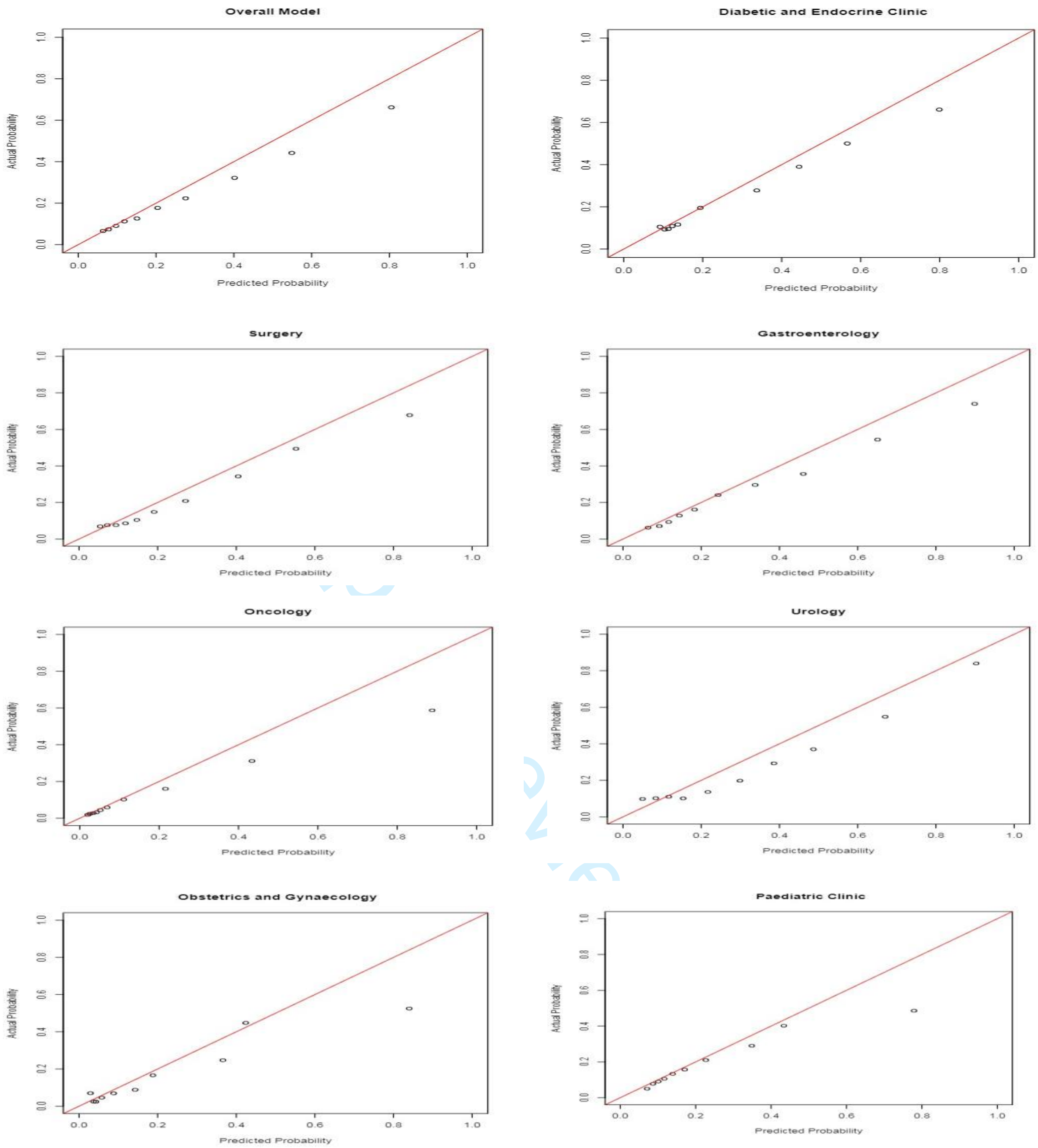
Figure legend:

Figure 1: Calibration curves of the overall model and by clinic
Red line indicates a reference line where predicted and observed probabilities are equal (prefect calibration). Each point indicates the predicted and observed probability of missed hospital appointments in each of the 10 stratum. Point below the reference line indicate over-prediction and above the line indicates under- prediction



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Supplementary Table 1: Development and validation dataset used in the prediction models development by clinic

Model	Development		Validation		Total
	Missed	Attended	Missed	Attended	
Overall model†	105869	354617	26444	88742	575672
Diabetic & Endocrine	21751	65604	5593	16410	109358
Surgery	16262	54559	4032	13635	88488
Urology	12371	31157	3098	7974	54000
Oncology	8158	50749	2023	12815	73745
Gastroenterology	7430	20567	1855	5031	34883
Paediatrics	34646	137299	8562	34218	214725
Obstetrics and Gynaecology	20949	104381	5407	26230	156967

†Includes all clinics except Paediatric clinic and Obstetrics & Gynaecology clinic

Supplementary Table 2: Average daily number of appointments per clinic

Clinic†	Number of appointments
Diabetic and Endocrine	73
Surgery	58
Urology	45
Oncology	48
Gastroenterology	24
Paediatric	137
Obstetrics and Gynaecology	102

†Top seven clinics with the highest missed hospital appointment rate and number of scheduled appointments.

Supplementary Table 3: Overall characteristics of the datasets for the top seven clinics.

	Diabetic & Endocrine	Surgery	Urology	Oncology	Gastroenterology	Paediatric	Obstetrics & Gynaecology
	N=109358	N=88488	N= 54600	N=73745	N= 34883	N=214725	N=156967
Appointment Status							
Attended	82014 (74.0)	68194 (77.1)	39131 (71.7)	63564 (86.2)	25598 (73.4)	171517 (79.9)	130611 (83.2)
Missed	27344 (25.0)	20294 (22.9)	15469 (28.3)	10181 (13.8)	9285 (26.6)	43208 (20.1)	26356 (16.8)
Sex							
Female	76872 (70.3)	52915 (59.8)	12240 (22.4)	50022 (67.8)	17410 (49.9)	92820 (43.2)	156967 (100.0)
Male	32486 (29.7)	35573 (40.2)	42360 (77.6)	23723 (32.2)	17473 (50.1)	121905 (56.8)	0 (0.0)
Age (mean (SD))	40.51 (12.77)	45.34 (15.98)	51.47 (17.67)	52.32 (14.96)	42.72 (14.[illegible]4)	6.49 (5.22)	33.67 (8.28)
Appointment Day							
Sunday	25547 (23.4)	18118 (20.5)	13475 (24.7)	16364 (22.2)	6652 (19.1)	43432 (20.2)	29036 (18.5)
Monday	20995 (19.2)	19084 (21.6)	0 (0.0)	10815 (14.7)	11420 (32.7)	46391 (21.6)	34290 (21.8)
Tuesday	24353 (22.3)	18464 (20.9)	13775 (25.2)	17813 (24.2)	2662 (7.6)	41550 (19.4)	33782 (21.5)
Wednesday	22555 (20.6)	19414 (21.9)	13983 (25.6)	17901 (24.3)	5513 (15.8)	43604 (20.3)	33064 (21.1)
Thursday	15908 (14.5)	13408 (15.2)	13367 (24.5)	10852 (14.7)	8636 (24.8)	39748 (18.5)	26795 (17.1)
Appointment Month							
January	10182 (9.3)	8624 (9.7)	5398 (9.9)	7356 (10.0)	3692 (10.6)	21533 (10.0)	15272 (9.7)
February	9305 (8.5)	8119 (9.2)	4943 (9.1)	6711 (9.1)	3460 (9.9)	20605 (9.6)	15036 (9.6)
March	9900 (9.1)	7812 (8.8)	5037 (9.2)	6509 (8.8)	3307 (9.5)	18369 (8.6)	14663 (9.3)
April	9798 (9.0)	7412 (8.4)	4749 (8.7)	6258 (8.5)	3030 (8.7)	18086 (8.4)	13239 (8.4)
May	9866 (9.0)	7748 (8.8)	4758 (8.7)	6411 (8.7)	3214 (9.2)	18325 (8.5)	13763 (8.8)
June	7440 (6.8)	6347 (7.2)	3963 (7.3)	5346 (7.2)	2501 (7.2)	14699 (6.8)	11366 (7.2)
July	8650 (7.9)	6130 (6.9)	3963 (7.3)	5491 (7.4)	2372 (6.8)	15303 (7.1)	10543 (6.7)
August	7846 (7.2)	6725 (7.6)	4405 (8.1)	6048 (8.2)	2618 (7.5)	15316 (7.1)	10913 (7.0)
September	8290 (7.6)	6776 (7.7)	4043 (7.4)	5605 (7.6)	2859 (8.2)	17131 (8.0)	12240 (7.8)
October	9851 (9.0)	7865 (8.9)	4536 (8.3)	6084 (8.3)	2819 (8.1)	19045 (8.9)	13495 (8.6)
November	8785 (8.0)	7116 (8.0)	4291 (7.9)	5618 (7.6)	2364 (6.8)	17392 (8.1)	12978 (8.3)
December	9445 (8.6)	7814 (8.8)	4514 (8.3)	6308 (8.6)	2647 (7.6)	18927 (8.8)	13459 (8.6)

Marital Status							
Child (<13Years Old)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	175840 (81.9)	0 (0.0)
Single	25551 (23.4)	17290 (19.5)	11286 (20.7)	7949 (10.8)	8732 (25.0)	25385 (11.8)	14568 (9.3)
Married	68618 (62.7)	56865 (64.3)	36104 (66.1)	50316 (68.2)	21259 (60.9)	415 (0.2)	133031 (84.8)
Divorced	647 (0.6)	663 (0.7)	241 (0.4)	438 (0.6)	234 (0.7)	20 (0.0)	473 (0.3)
Widow	919 (0.8)	992 (1.1)	260 (0.5)	847 (1.1)	246 (0.7)	0 (0.0)	335 (0.2)
Missing	13623 (12.5)	12678 (14.3)	6709 (12.3)	14195 (19.2)	4412 (12.6)	13065 (6.1)	8560 (5.5)
Governorate							
Muscat	67945 (62.1)	49496 (55.9)	25634 (46.9)	30980 (42.0)	19959 (57.2)	90519 (42.2)	122871 (78.3)
South Batina	665 (0.6)	1430 (1.6)	488 (0.9)	2683 (3.6)	420 (1.2)	4764 (2.2)	615 (0.4)
AL Dhakiliya	618 (0.6)	435 (0.5)	286 (0.5)	692 (0.9)	152 (0.4)	1402 (0.7)	284 (0.2)
North Batina	1484 (1.4)	842 (1.0)	708 (1.3)	1105 (1.5)	439 (1.3)	2841 (1.3)	952 (0.6)
North Sharqiya	8366 (7.7)	6922 (7.8)	5393 (9.9)	7866 (10.7)	2627 (7.5)	24596 (11.5)	5581 (3.6)
South Sharqiya	8633 (7.9)	7520 (8.5)	3750 (6.9)	10412 (14.1)	2682 (7.7)	24188 (11.3)	4536 (2.9)
AL Dhahira	9429 (8.6)	7472 (8.4)	5831 (10.7)	6979 (9.5)	3930 (11.3)	23099 (10.8)	14288 (9.1)
AL Buriami	3687 (3.4)	4856 (5.5)	5676 (10.4)	4211 (5.7)	1422 (4.1)	15407 (7.2)	2760 (1.8)
AL Wusta	5016 (4.6)	5187 (5.9)	3772 (6.9)	3641 (4.9)	1640 (4.7)	14540 (6.8)	2805 (1.8)
Musandam	3281 (3.0)	3761 (4.3)	2682 (4.9)	4797 (6.5)	1452 (4.2)	11799 (5.5)	2120 (1.4)
Dhofar	234 (0.2)	567 (0.6)	369 (0.7)	373 (0.5)	159 (0.5)	1505 (0.7)	150 (0.1)
GCC Countries	0 (0.0)	0 (0.0)	11 (0.0)	6 (0.0)	1 (0.0)	65 (0.0)	5 (0.0)
Service Cost							
Pay visit and registration fees¥	103881 (95.0)	83928 (94.8)	51255 (93.9)	66992 (90.8)	33284 (95.4)	130591 (60.8)	152055 (96.9)
< 2 Years old*	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	68092 (31.7)	0 (0.0)
Pay all medical service fees†	3069 (2.8)	2898 (3.3)	2020 (3.7)	5736 (7.8)	870 (2.5)	5775 (2.7)	4221 (2.7)
Under Social Affair coverage*	2408 (2.2)	1662 (1.9)	1325 (2.4)	1017 (1.4)	729 (2.1)	10267 (4.8)	691 (0.4)
Appointment waiting group							
< 30 Days	63310 (57.9)	36907 (41.7)	16907 (31.0)	36606 (49.6)	6422 (18.4)	53131 (24.7)	85710 (54.6)
> 30 ≤ 60 Days	14582 (13.3)	18908 (21.4)	5742 (10.5)	8314 (11.3)	5327 (15.3)	24570 (11.4)	36865 (23.5)
> 60 ≤ 90 Days	10646 (9.7)	15329 (17.3)	5020 (9.2)	10586 (14.4)	5519 (15.8)	30480 (14.2)	13051 (8.3)
> 90 ≤ 120 Days	9019 (8.2)	5610 (6.3)	5811 (10.6)	7833 (10.6)	4106 (11.8)	25466 (11.9)	7285 (4.6)
> 120 Days	11801 (10.8)	11734 (13.3)	21120 (38.7)	10406 (14.1)	13509 (38.7)	81078 (37.8)	14056 (9.0)
Nationality							
Omani	104604 (95.7)	84106 (95.0)	51768 (94.8)	66842 (90.6)	33541 (96.2)	207783 (96.8)	149034 (94.9)
Non-Omani	4754 (4.3)	4382 (5.0)	2832 (5.2)	6908 (9.4)	1342 (3.8)	6942 (3.2)	7933 (5.1)

Prior visit group							
Zero prior appointment	9670 (8.8)	20892 (23.6)	17949 (32.9)	5728 (7.8)	7302 (20.9)	52185 (24.3)	36673 (23.4)
One prior appointment	8736 (8.0)	14884 (16.8)	11051 (20.2)	5420 (7.3)	5361 (15.4)	33041 (15.4)	26375 (16.8)
Two prior appointments	7466 (6.8)	10851 (12.3)	6645 (12.2)	4934 (6.7)	3892 (11.2)	22372 (10.4)	19194 (12.2)
Three prior appointments	6479 (5.9)	8051 (9.1)	4411 (8.1)	4573 (6.2)	2963 (8.5)	16483 (7.7)	14544 (9.3)
Four prior appointments	5716 (5.2)	6085 (6.9)	3082 (5.6)	4325 (5.9)	2398 (6.9)	12749 (5.9)	11334 (7.2)
Five prior appointments	5044 (4.6)	4697 (5.3)	2242 (4.1)	4018 (5.4)	1887 (5.4)	10224 (4.8)	8884 (5.7)
> Five prior appointments	66247 (60.6)	23028 (26.0)	9220 (16.9)	44747 (60.7)	11080 (31.8)	67671 (31.5)	39963 (25.5)

¥ Omani citizens, GCC citizens, Expatriate works for government. Expatriate married to Omani. * Exempted from visit and registration fees. †Expatriates pay all medical fees (service fees, visit fees, registration fees).

Supplementary Table 4: Overbooking approaches simulation outcomes for the difference between attended appointments and daily available appointments based on the 1000 iterations by clinic

Clinic	Diabetic and Endocrine			Surgery			Urology			Oncology		
Overbooking approach	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero	Positive
5 %	0	0	1000	0	0	1000	0	0	1000	9	19	972
10 %	0	0	1000	2	0	998	1	0	999	133	116	751
15%	2	2	996	9	21	970	4	8	988	367	141	492
20%	20	24	956	84	56	860	17	26	957	734	115	151
25%	84	61	855	188	81	731	53	46	901	891	50	59
30%	297	100	603	401	113	486	170	98	732	966	17	17
35%	577	92	331	652	94	254	292	104	604	997	2	1
40%	763	72	165	840	60	100	451	115	434	1000	0	0
Prediction Model	104	47	849	133	75	792	93	71	836	290	170	540
Clinic	Gastroenterology			Paediatric			Obstetrics and Gynaecology					
Overbooking approach	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero	Positive			
5 %	2	3	995	0	0	1000	0	0	1000			
10 %	4	15	981	0	0	1000	9	6	985			
15%	46	62	892	9	4	987	104	57	839			
20%	99	88	813	93	36	871	422	110	468			
25%	146	154	700	428	74	498	840	59	101			
30%	246	174	580	803	59	138	962	13	25			
35%	383	149	468	973	6	21	996	2	1			
40%	581	149	270	996	2	2	1000	0	0			
Prediction Model	171	138	691	93	47	860	182	80	738			

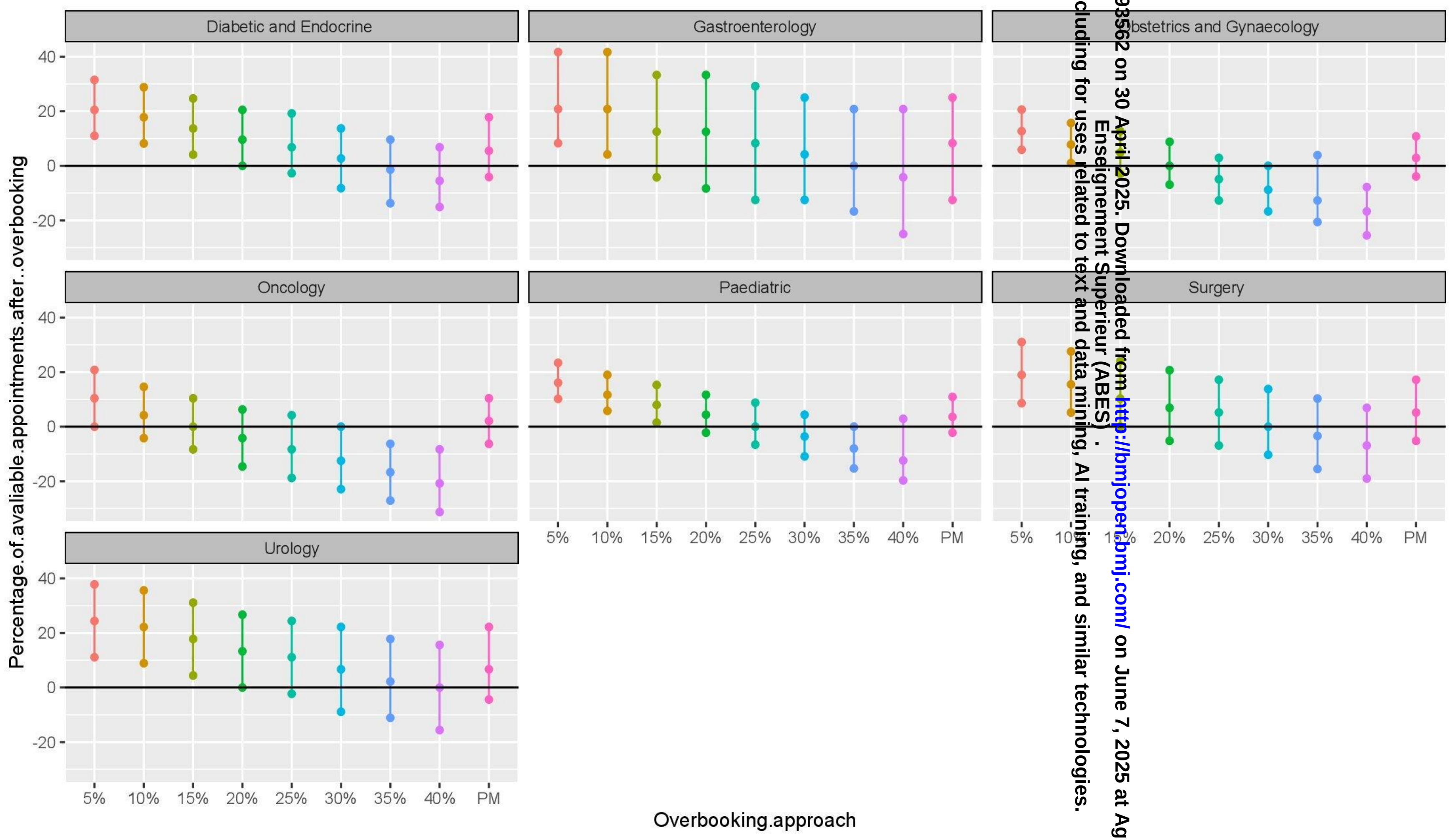
Negative: proportion of iterations when attended appointments exceed daily available appointments (clinic overburden). Zero: proportion of iterations when attended appointment equal to daily available appointment (all appointments are taken). Positive: proportion of iterations when daily available appointments exceed attended appointments (clinic underutilized)(Extra appointments can be scheduled)

Supplementary Table 5: Distribution analysis of the difference between attended appointments and daily available appointments based on the 1000 iterations for different overbooking approaches by clinic

Clinic	Diabetic & Endocrine				Surgery				Urology				Oncology			
Overbooking approach	Min	Mean	Max	Variance	Min	Mean	Max	Variance	Min	Mean	Max	Variance	Min	Mean	Max	Variance
5 %	5	15	27	13	1	11	23	11	1	11	22	[illegible]	-2	5	13	6
10 %	2	13	25	14	-3	9	20	11	-1	10	20	[illegible]	-5	2	13	6
15%	-2	10	23	14	-3	7	21	12	-4	8	18	[illegible]	-6	0	9	7
20%	-5	7	19	15	-7	4	16	13	-3	6	18	[illegible]	-9	-2	8	7
25%	-5	5	20	17	-9	3	15	13	-6	5	16	[illegible]	-11	-3	6	7
30%	-9	2	14	17	-12	0	13	14	-8	3	16	[illegible]	-13	-5	3	7
35%	-12	-1	13	18	-14	-1	12	14	-8	1	14	[illegible]	-16	-8	1	7
40%	-17	-3	13	18	-17	-4	10	14	-11	0	11	[illegible]	-18	-9	-1	8
Prediction Model	-6	5	19	16	-6	3	14	11	-7	4	15	[illegible]	-6	1	7	5

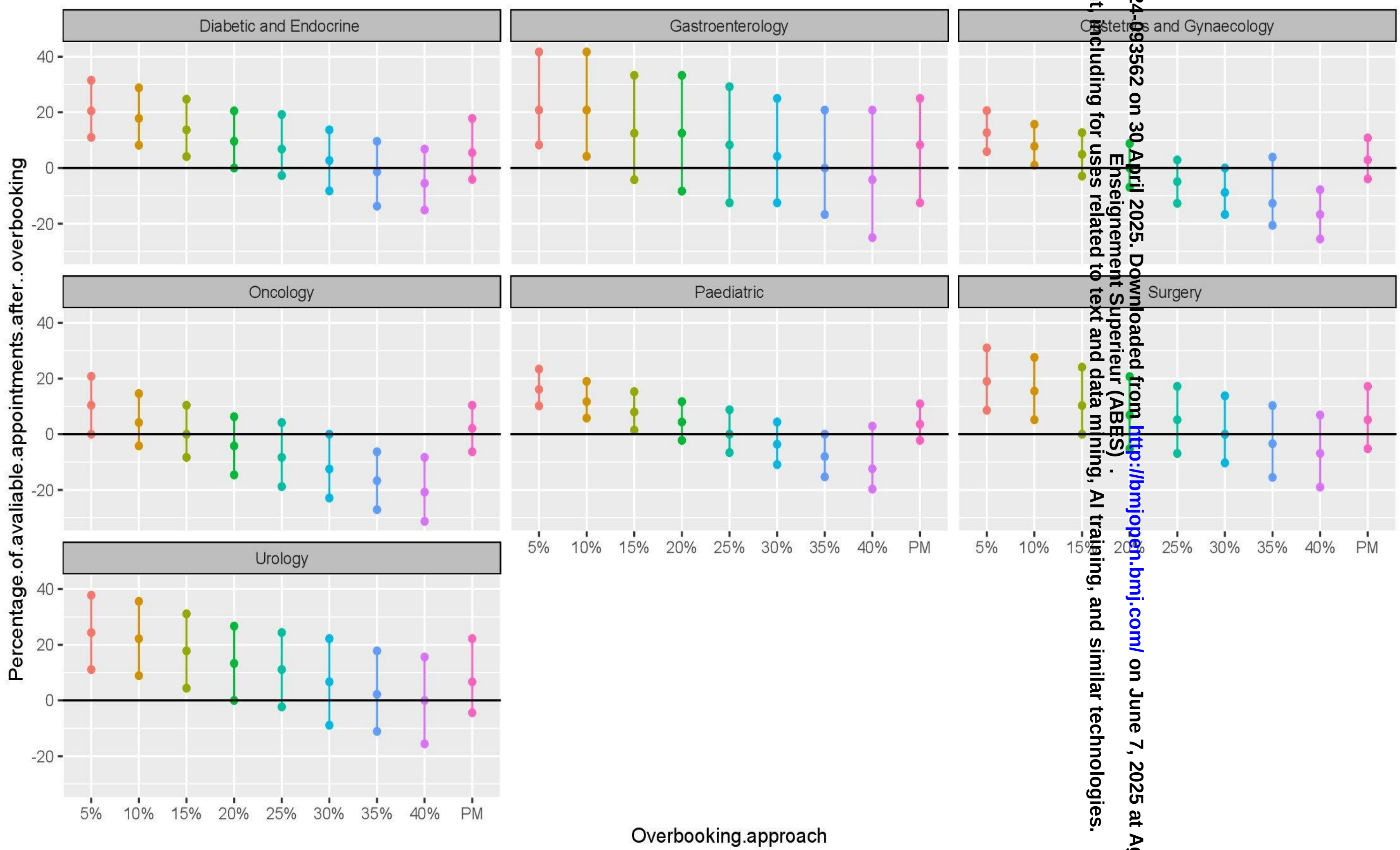
Overbooking approach	Gastroenterology				Paediatric				Obstetrics and Gynaecology			
	Min	Mean	Max	Variance	Min	Mean	Max	Variance	Min	Mean	Max	Variance
5 %	-1	6	14	5	9	22	36	22	2	13	30	15
10 %	-2	5	13	5	3	16	32	24	-1	9	25	16
15%	-4	3	12	6	-2	11	26	24	-6	5	19	16
20%	-4	3	12	6	-8	6	22	25	-13	0	19	17
25%	-6	2	12	6	-12	1	17	27	-17	-4	13	16
30%	-5	1	9	6	-19	-5	11	28	-23	-8	7	[illegible]
35%	-7	0	8	6	-25	-10	7	29	-24	-12	8	[illegible]
40%	-9	-1	7	7	-32	-16	3	32	-29	-17	-2	26
Prediction Model	-5	2	10	5	-7	6	21	22	-7	3	19	14

Negative: proportion of iterations when attended appointments exceed daily available appointments (clinic overburden). Zero: proportion of iterations when attended appointment equal to daily available appointment (all appointments are taken). Positive: proportion of iterations when daily available appointments exceed attended appointments (clinic underutilized)(Extra appointments can be scheduled)



Supplementray Figure 1 : Feasability of different overbooking approaches by clinic

PM: Prediction Model



Supplementray Figure 1 : Feasability of different overbooking approaches by clinic

PM: Prediction Model