ST VINCENT'S HOSPITAL
MELBOURNE
A FACILITY OF ST VINCENT'S HEALTH AUSTRALIA

AI-enabled Patient Journey Acceleration in Hospital in the Home

Using machine learning to find @home patients

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SVHM Decision Support Unit
October 2023

Under the stewardship of Mary Aikenhead Ministries

Getting to know us

Bede McKenna

- Acting Manager Decision Support Unit
- Interested in technical solutions to hospital problems
- Not a data scientist or AI/ML expert

Getting to know us

Corinne Howell

- BNSc, RN, Grad Cert FLM, Grad Cert Clin Nur (Acute Med)
- Senior RN experienced in Acute, Subacute, Residential and @Home
- Early adopter of DataRobot and very recently the NUM of HITH
- Intermediate technological skill level

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Aim

- To introduce you to the idea of using machine learning in healthcare to augment human performance
- To create efficiency in current systems that protects clinician time and ultimately supports better patient journeys
- To inspire you to think about where this could be useful for you in your work

Agenda

Context → Provoking change → Demography → Why AI? → How AI? →

Methodology → Results → Demo → Integrating AI → Current state →

Review → Key takeaways → Q&A

Context

Context	▪ As part of a plan for digital innovation SVHA implemented an accelerated innovation process in the form of a "100-Day Digital Challenge" ▪ The Decision Support Unit (DSU) is SVHM primary source of data analysis and reporting ▪ SVHM does not yet have an EMR, clinical information is housed across various systems and progress notes are often handwritten ▪ SHVM has a partnership with a company providing automated machine learning operations
Trigger	▪ As part of the "100-Day Digital Challenge" DSU were asked to design and implement a "digital solution" that would help in the identification of patients suitable for @home care.
Question	▪ **Is it possible for us to predict, and notify clinical staff of, the patients in our hospital who are suitable for @home care?**

Provoking Change

- Why the focus on home?
- How do we know which patients?
- How do we identify them?

DEMOGRAPHICS

Chronological Age
- Average: 61
- Range: 19-90
- Median: 67

Career Age
- 73% >6 years since graduation
- most have post grad certs (minimum)

Conditions in HITH
- Total joint replacement
- Mastectomy
- Plastics reconstruction
- Diabetic foot
- Infection:
  - OM
  - Urosepsis

Length of Stay

Avg LoS currently 7 days with range being 24 hours to 6 weeks

Rx in HITH
- IVABs
- IV antifungals
- IV diuresis
- TPN
- vacuum-assisted wound closure

Staffing profile
- Avg nurse is crit care certified
- 7/10 female

Staffing Profile
- 64% crit care certified nurses
- 7/10 female
- patient assessment strongest skill

64%

Physicians + Pharmacists + Physiotherapists + Admin + Intake

Why AI?

If we were to manually patient-scout, it might take 7 work days to find all suitable candidates:

- 508 patients
- 5 apps per patient = 7 mins reading
- Limited chance of "finding" suitable patients e.g. needle in a haystack
- Average LoS approx. 7 days

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Using structured data – early challenges

Output of workshop: Proxies for suitability for @home care and associated data challenges

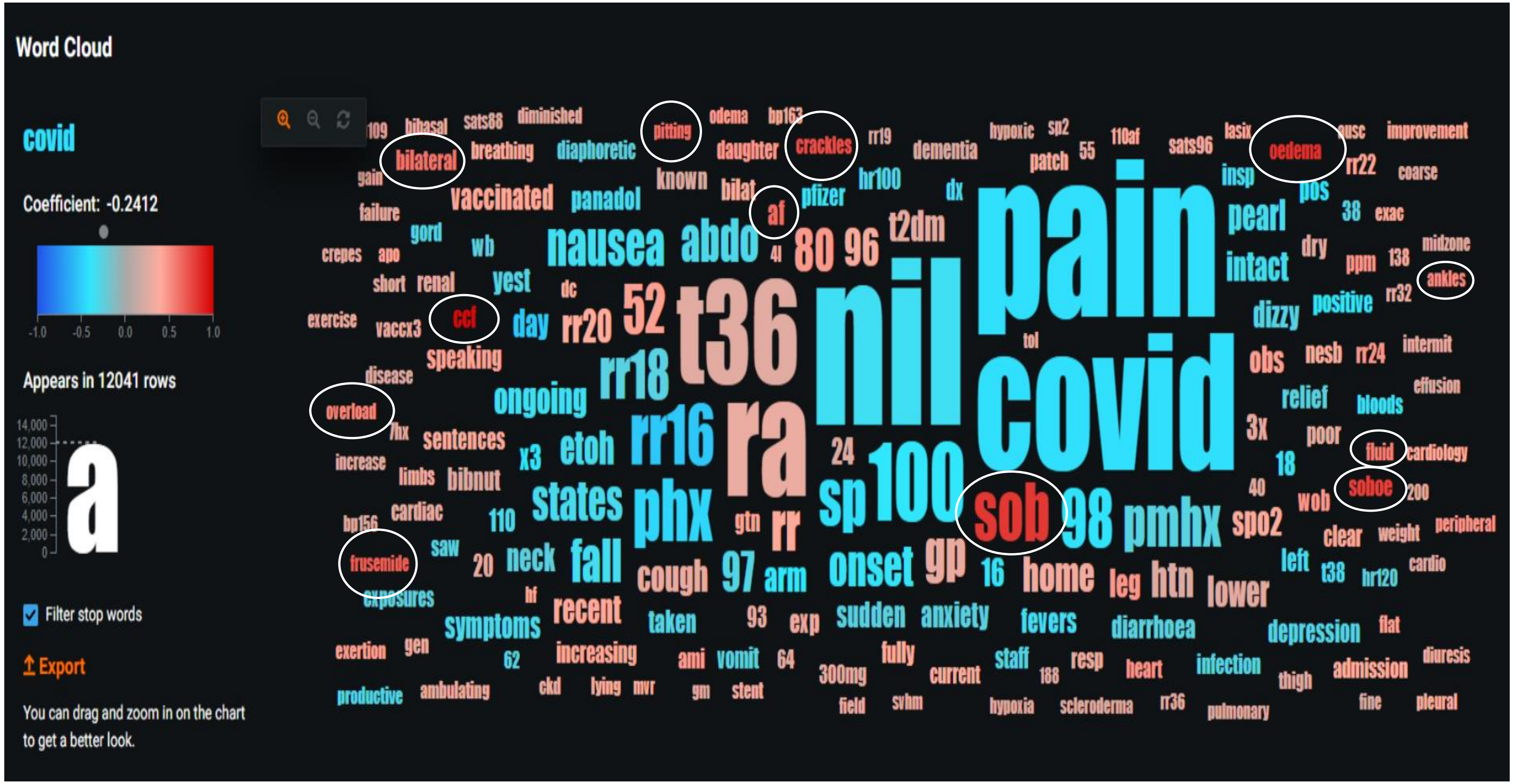
			Potential ED data source		Data source and potential proxy definition				
Discharge Dx (number = case numbers	Specific HITH Clinical Cohorts to target 1	Treatment provided by HITH/@ home service 2	ED Discharge Diagnosis that may be a proxy indicator (*please note: not entered until patient is discharged from ED*)	ED free text word / phrase that may be found in ED PAS notes (*please note: likely to be close to/in real time*) 3	Pharmacy 4	Pathology 5	Radiology	PAS *e.g. previous @ home admission; patient condition*	OTHER requirements for @home service
1459	Cellulitis	IV Abx in community	Cellulitis Of Leg (Excludes Cellulitis Of Toe: L0302) Boil / Furunculosis / Abscess, Skin, Any Site Cellultis, Skin (Excludes Cellulitis of Leg: L0311, Toe: L0302 Or Fin Cellulitis of Arm (Excludes Cellulitis of Finger: L0301) Skin Infection	cellulitis cephazolin / cefazolin flucloxacillin IV Abx red, painful, hot extremity		N/A	N/A		
1015	Heart Failure/CCF	For IV diuresis in community	Congestive Heart Failure Cardiomyopathy Pleural Effusion Pulmonary Oedema, Acute Peripheral Oedema	IV frusemide furosemide lasix frusemide (not necessarily IV) SOB, peripheral oedema SOBOE		? BNP 300 ABGs VBGs		involved with heart failure team eg HIP	no new oxygen requirements
34	Infective Endocarditis	For IV Abx in community	Endocarditis	IE endocarditis infec. Endocarditis PICC line			PICC line TOE/TTE		
bacteruria/UTI/urosepsis 563, cystitis 315	Pyelonephritis	For IV Abx in community	Pyelonephritis	ESBL urosepsis UTI		ESBL	*? Renal US or CT findings*		
bacteruria/UTI/urosepsis 563, cystitis 315	UTI	For IV Abx in community	Bacteriuria / Urinary Tract Infection (Uti) / Urinary Sepsis Cystitis						
84	Septic arthritis	For IV Abx in community	Osteomyelitis Arthritis, Infective	washout/admission joint aspirate positive culture		*? Joint aspirate findings/ or cell count + culture (culture can take a few*	ultrasound findings?	theatre list - washout, osteomyelitis nursing handover on EPJB	
0	Anti-coagulation (inc. bridging anticoag.)	For anti-coagulation in community		therapeutic clexane on warfarin thrombus DVT PE sub therapeutic supra therapeutic	vitamin K		*?US DVT or CTPA PE + clexane*	pre-procedural - flagged via peri-op	

Challenges with this approach:

1. The first column in this matrix is "diagnosis" – a field that is not populated until a patient is discharged (or leaves ED), making it **near impossible to apply the next criteria in real-time**.
2. Similarly, treatments are **not captured anywhere in a structured way**, so these can't easily be used as proxies.
3. **"hard-coding"** keywords to look for is rarely exhaustive due to variations in spelling, acronyms, etc.
4. No system at SVHM provides consistent enough prescription / administration data for this exercise.
5. Pathology / Radiology data feeds are unavailable for us to use at present.

Unstructured (free-text) clinical data and a machine learning platform

Heart failure: Triage note word cloud representing frequency and strength of association with diagnosis



- In this word cloud, the size of words represent their frequency in triage notes, but their **colour** (from blue to red) represent the **strength and direction of their association with heart failure**.
- Darker red words have a strong positive correlation with heart failure, such as **"CCF", "oedema", "SOB", "SOBOE", "crackles", "frusemide", "AF", "pitting"**, etc.
- The combination of words in triage comments and their relative coefficients (both positive and negative) contribute to **an overall prediction score, from 0 to 100%** estimated probability.

While this allowed us to utilise unstructured data, our initial classification models perpetuated a historic bias against @home

The model will replicate the goal set in its training data, this goal needs to be aligned with our intention…

Similar cases where the model was fed different outcomes

Presenting complaint	HITH
BIBA: 3/7 cellulitis to R)ankle extending up leg, seen GP yesterday & Oral ABs commenced, incur SOB for 24hrs with fevers & pain to site. crackles R)mid zone.hr 60 bp 120/60 rr 24 T)36.8 gcs 15 Hx: triple covid vax, CCF, copd, h.CHOL. multiple	N
r)lower limb cellulitis for a day, ?syncopal episodes twice this am - 'just woke up on the ground', feels sob since last night, t37.4, hr120, rr18, sats99%, gcs15, hx cov vax x2	Y

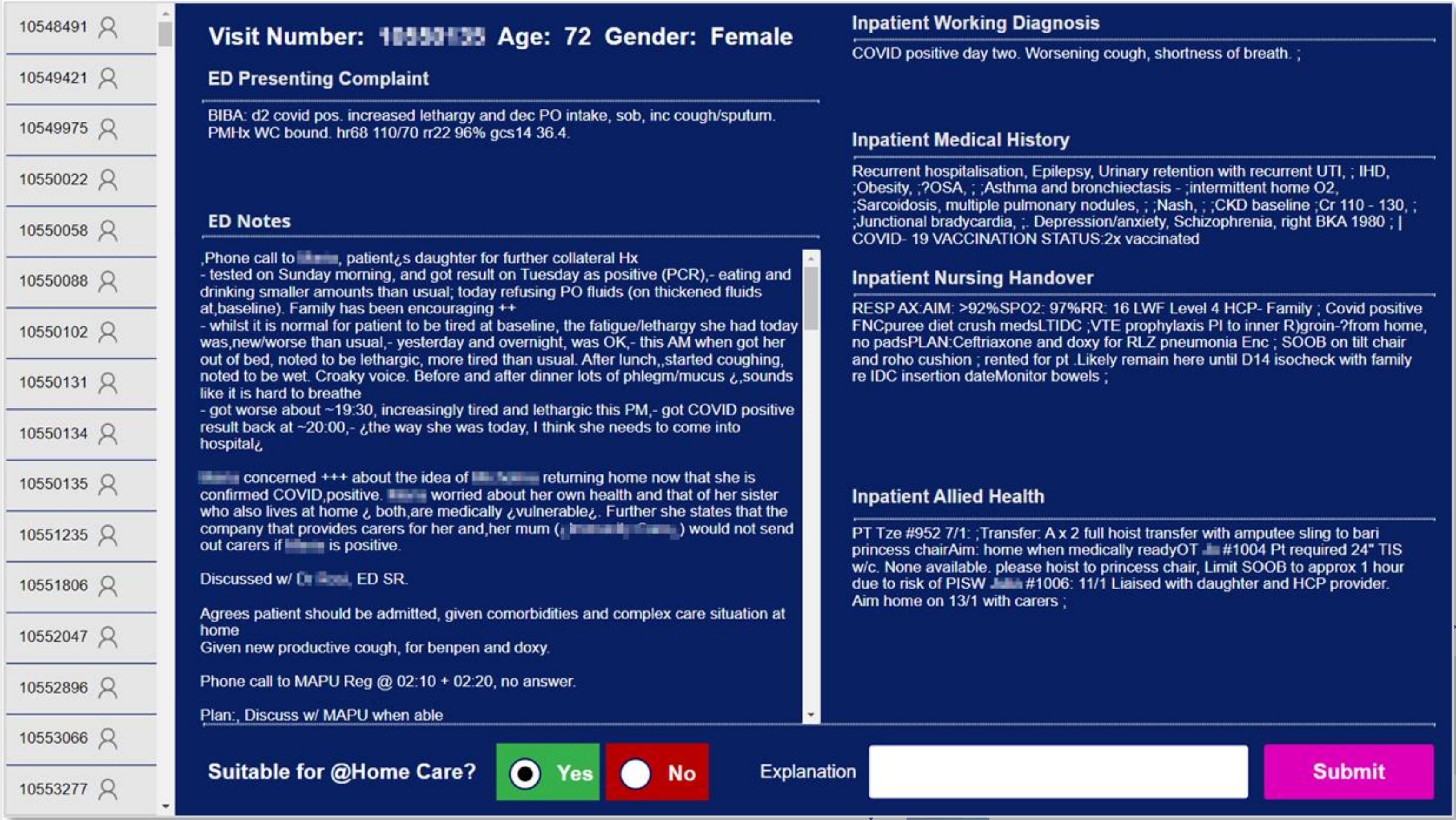
… the fact that many suitable cases had not utilised @home weakened our initial models

Model built on historic @home outcomes

	HITH	No HITH	Total
Positive	37	7	**43**
Negative	4	4634	**4638**
Total	**41**	**4641**	**4682**
Sensitivity = **84%;** PPV = **90%**			

We built an app to capture this training data that wasn't possible in our historic records

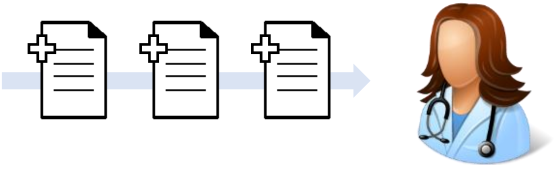
Screenshots from the app we developed to collect predictions from clinicians to train ML models

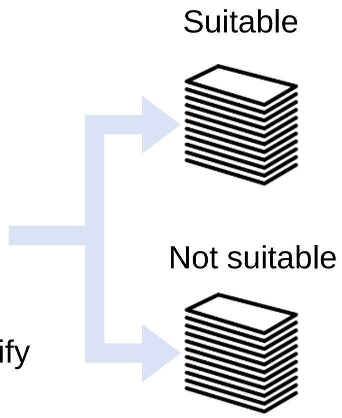


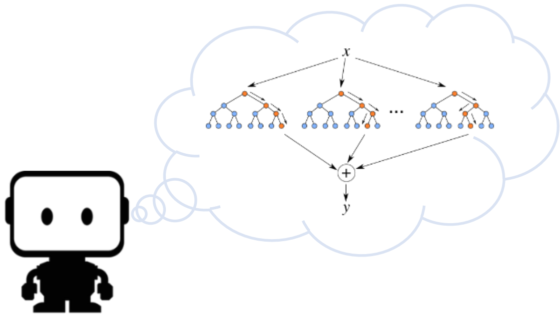
Our solution was to have clinicians sort 1,000 cases into “suitable” and “unsuitable” for HITH, and use this to train a model

Manually classifying data to create a “suitability for @Home Care” label for DataRobot

Step 1: Train model



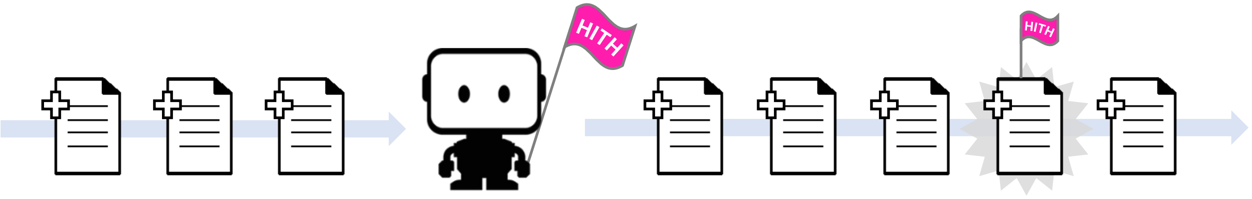




Clinicians review patient records and classify them into “suitable” or “not suitable” for @Home Care.

DataRobot studies the two groups and independently figures out how to distinguish them.

Step 2: Deploy model



DataRobot is fed live data and it flags patients it recognises as good candidates for @Home Care.

- In supervised machine learning, a computer algorithm is trained on input data that is labelled for a particular output.
- Unfortunately, we cannot use our historic “discharged by HITH” label, as we know we have been underutilising the service.
- Training DataRobot on this data would simply perpetuate the same rate of referrals to HITH.
- Instead, we will be asking clinicians to review 1,000 cases (a number consider reasonable for ML) in order to classify them into “suitable” or “not suitable” for @Home Care.
- This newly labelled data can be used to train DataRobot, so that it may begin to recognise and flag suitable candidates autonomously.

This new model performed well: we could replicate "human-level" performance…

Side-by-side: Among 998 cases classified by our clinicians, how many actually went to HITH vs how many would have been flagged by our model

"Human performance" - Patients who actually went to HITH

	HITH	No HITH	Total
Suitable[1]	42	236	**278**
Not suitable[1]	3	717	**720**
Total	**45**	**953**	**998**
Sensitivity = **15%;** PPV = **93%**			

"Machine performance" - Patients flagged by our algorithm

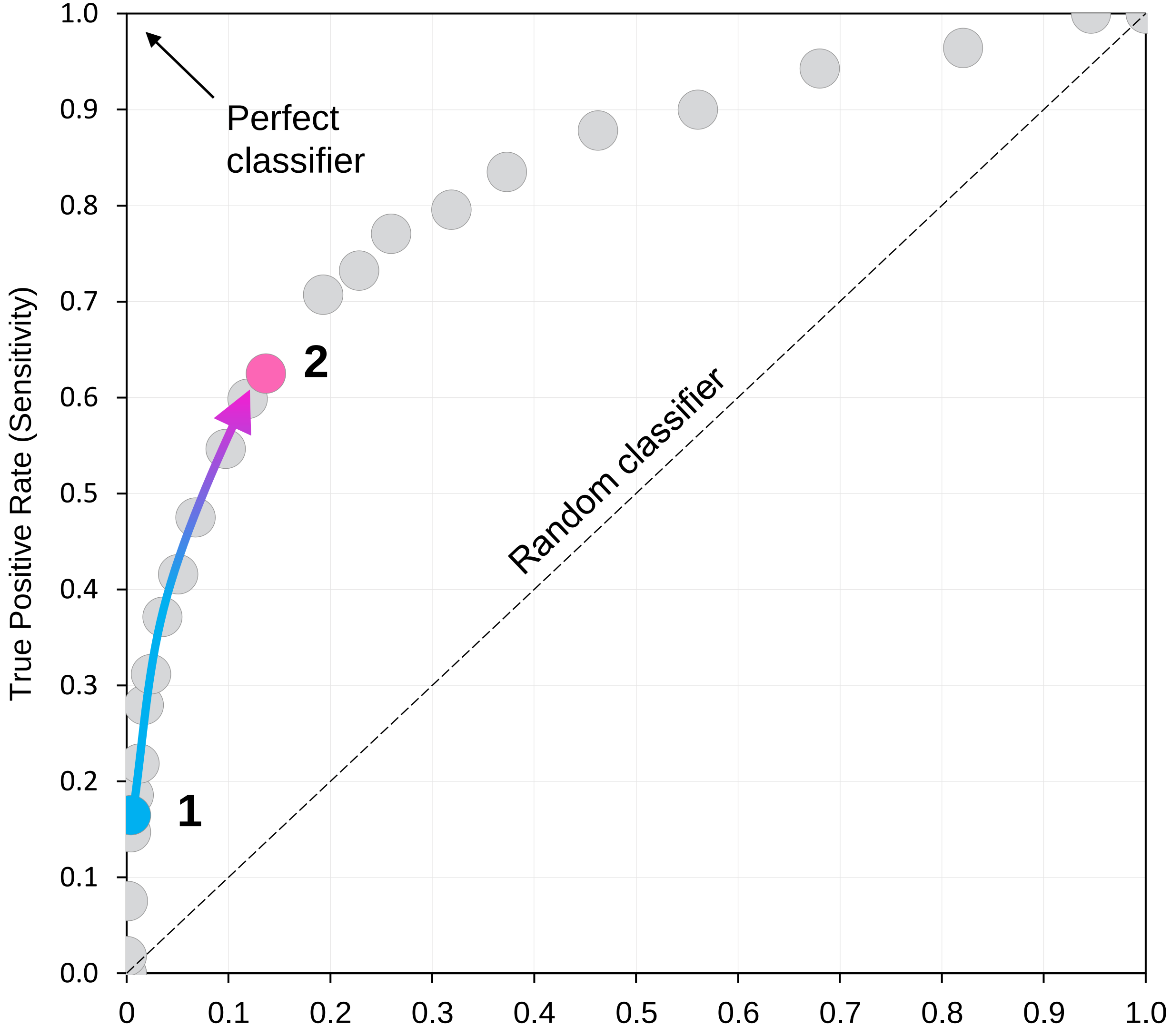
	Flagged	Not flagged	Total
Suitable[1]	46 (+4)	232 (-4)	**278**
Not suitable[1]	3	717	**720**
Total	**49**	**949**	**998**
@78% prediction threshold: Sensitivity = **17%**; PPV = **94%**			

- Of the 998 patients reviewed by our clinicians, 278 were classified as suitable for @home care.
- Of the 278, only 42 actually went to HITH, suggesting our "human system" has a very low sensitivity (15%) with high PPV (93%).
- By setting the strength of prediction threshold of our model quite high (78%), we can replicate the "human" level of performance.
- However, *this may not be the optimal setting*: we can change the prediction threshold to identify more suitable candidates for @home care.

1 As defined by our clinicians during their manual classification. 278 out of 998 patients reviewed were deemed "suitable" for @home care.

… and we could further improve our model's performance by tweaking its prediction threshold

ROC Curve – DataRobot 1a model



Interpretation

- Received operating characteristic (ROC) curves are graphical plots of the trade-off between sensitivity and false positive rate of classifier systems, at different prediction thresholds.
- A perfect classifier would be found in the top left corner (100% sensitivity, 0% false positive rate).
- A random classifier (no better than chance) would sit anywhere along the diagonal line (e.g. 50% sensitivity, but 50% false positive rate).
- Each dot on this plot represents the sensitivity and false positive rate of our model at different strength of prediction thresholds.
    1. **At position 1**, we set the threshold quite high (78%) yielding a very low false positive rate, but also a low sensitivity. This closely mimics "human" performance.
    2. **At position 2**, we lowered the threshold to 33%, resulting in a significant increase in sensitivity (62% vs 16%) for a modest increase in false positive rate (14% vs 0.4%).
- At this level of performance, **we are likely to start finding more suitable candidates for @home care**.

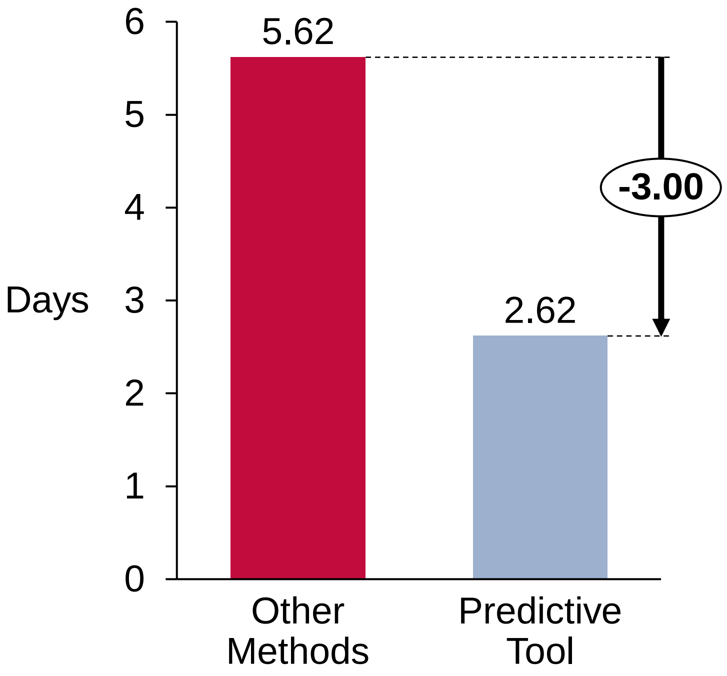
Demo

Standard daily work

These referrals are happening earlier in the admission and lowering the search time for clinicians

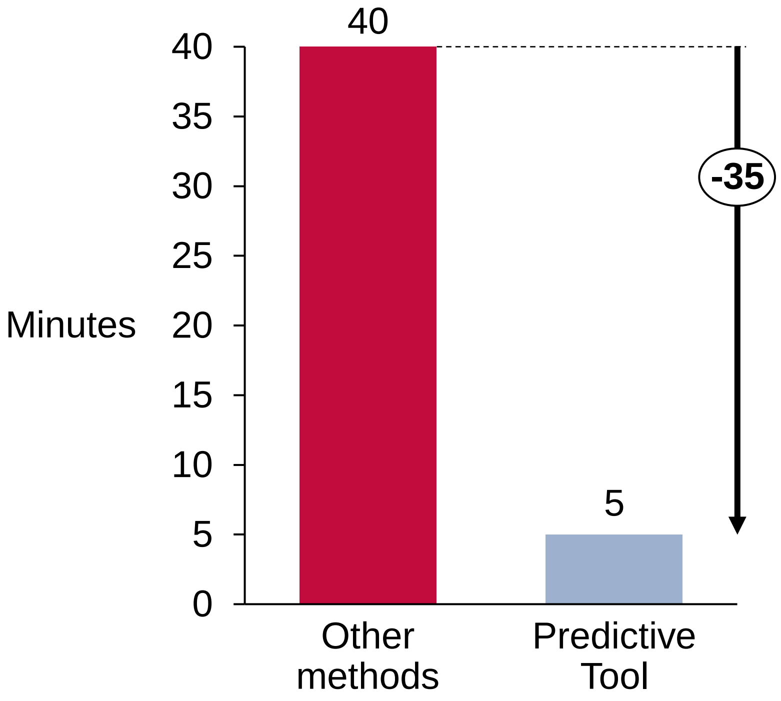
Referrals originating from the tool are happening on average 3 days earlier…

Avg days to referral by source



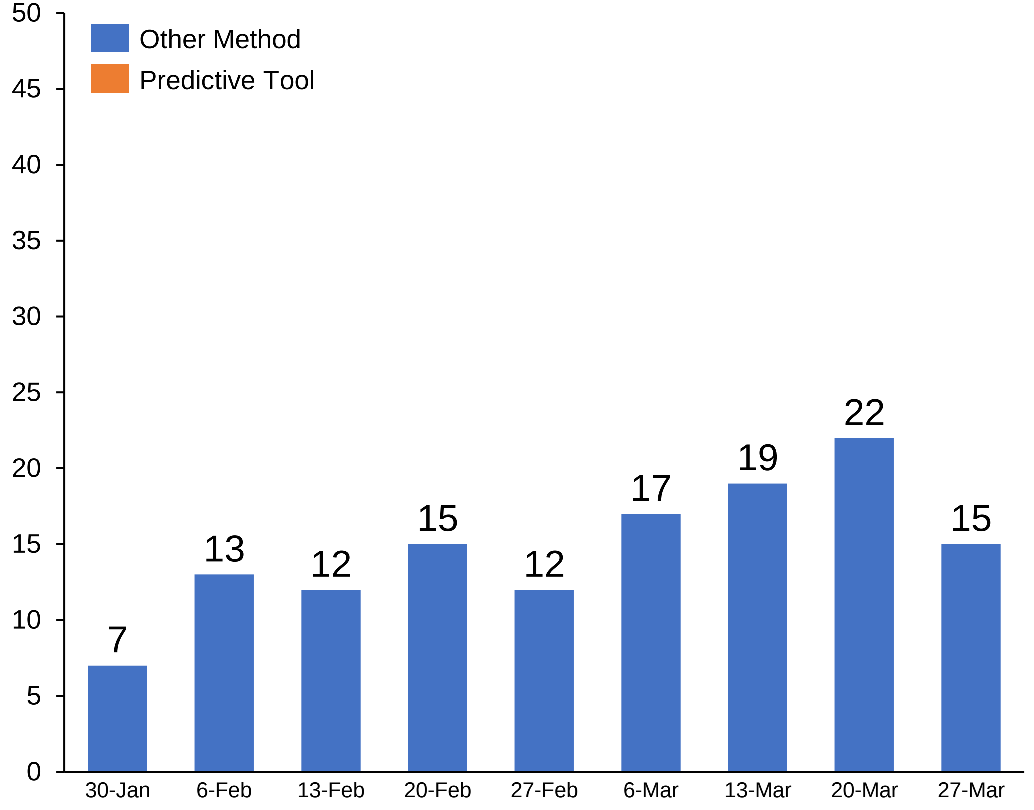
…and the time spent searching for patients has been massively decreased.

Minutes spent per case found

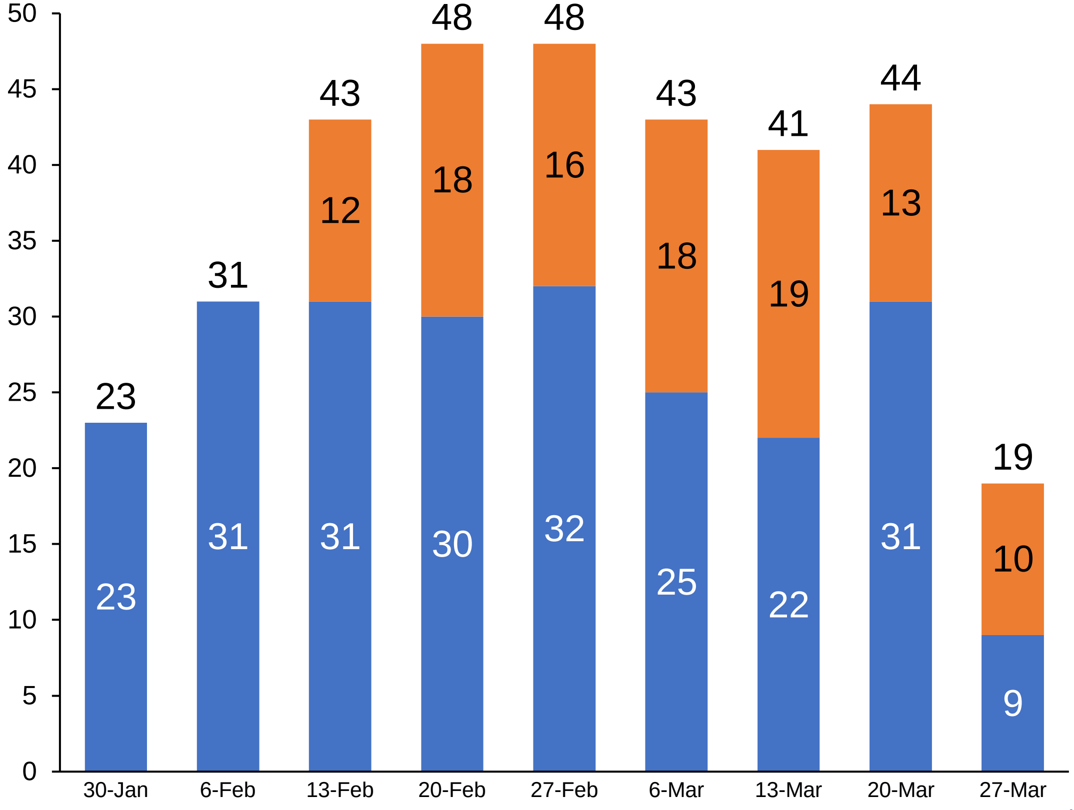


We are seeing an increase in referrals to HITH driven in part by use of our tool

Referrals to HITH: Feb-Mar 2022 (week start date Monday)



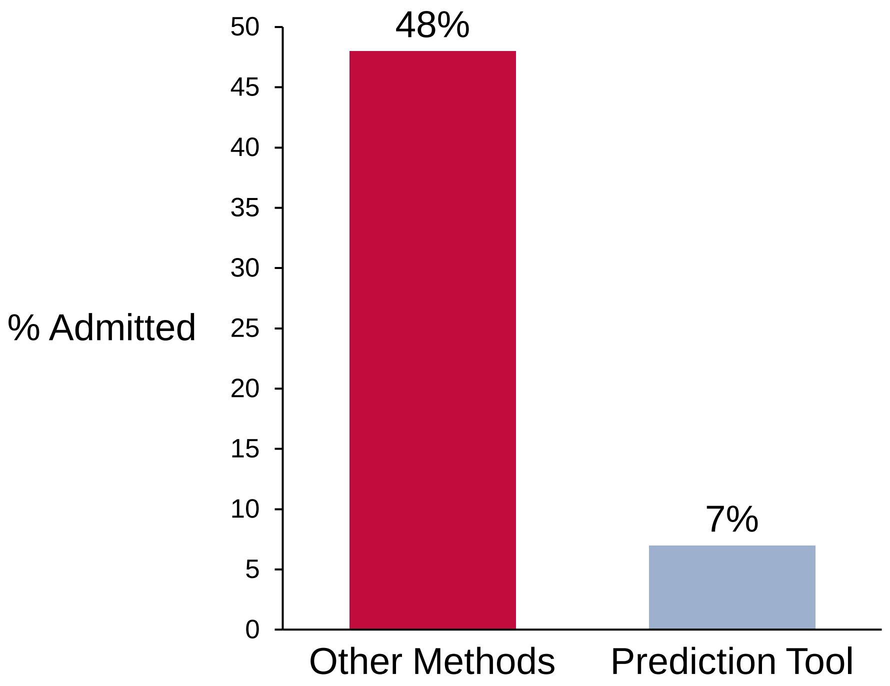
Referrals to HITH: Feb-Mar 2023 (week start date Monday)



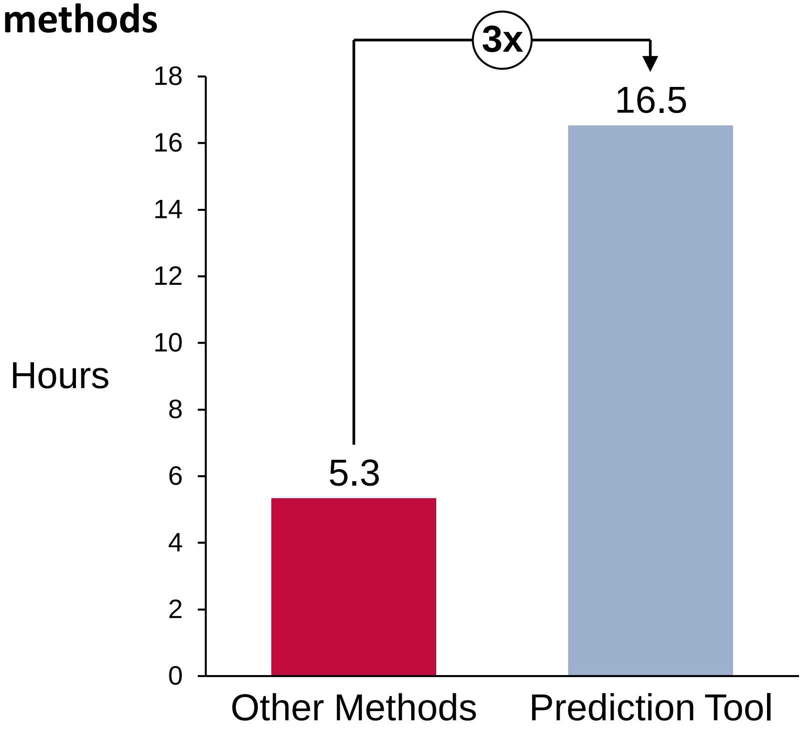
- From Feb 2023 onward referrals have increased by roughly 40% driven in part by prediction tool

However, we are finding that a lower proportion of these referrals are converting to a HITH admission

Referrals generated through the predictive tool have a significantly lower conversion to admission rate…



…additionally they spend three times longer waiting for review than referrals generated through other methods

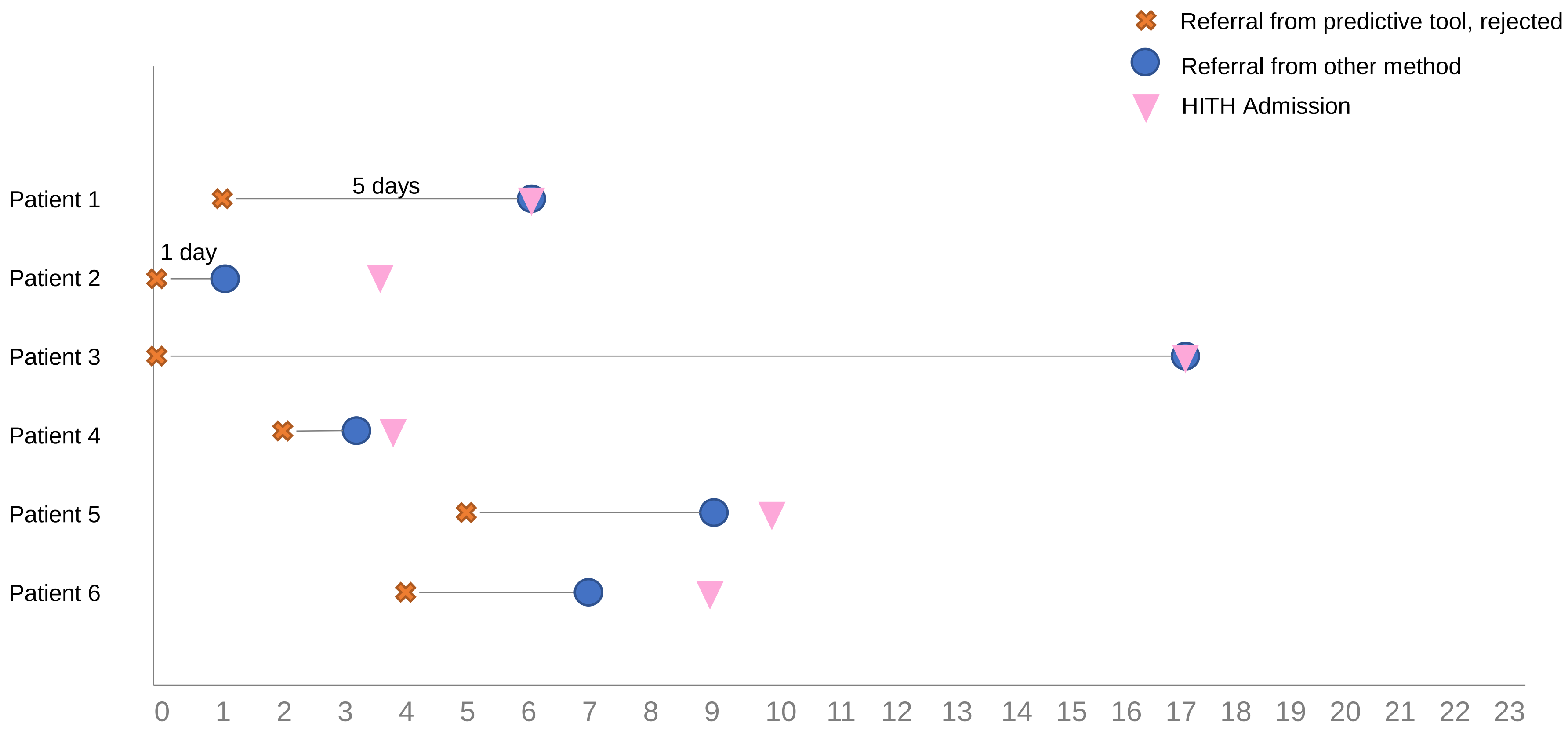


- A surprising number of the referrals clinicians refer from our predictive tool do not convert to HITH admissions
- There appears to be some difference in the way referrals from the predictive tool are treated compared to those found in other methods

Figures represent referrals generated through Feb-March 2023

Analysis of some rejected cases reveals they were in fact valid and timely, suggesting the issue may lie with process

Timelines of referrals and HITH admission, six patients Feb-Mar 2023



- There is a lower conversion for referrals generated through the predictive tool than other means.
- However a number of “failed” referrals were later found through other referral methods and became HITH conversion.
- Additionally limited lead time between referral and admission to HITH is a pain point for intake earlier referrals are valuable.
- There is further investigation needed to consider if other referrals from the predictive tool were closed inappropriately

While referral processes are assessed we continue to enhance and expand our predictive tool

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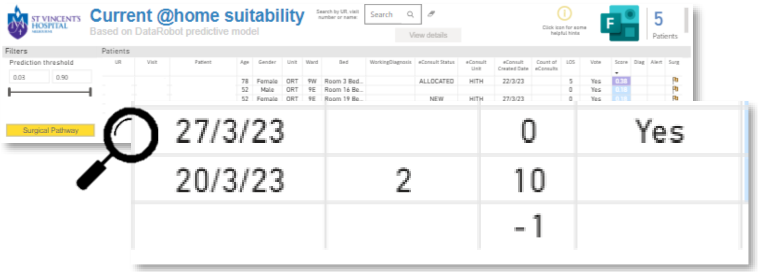
Task | **Description**

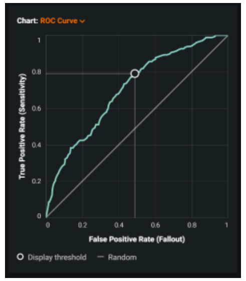
Done — Surgical patients

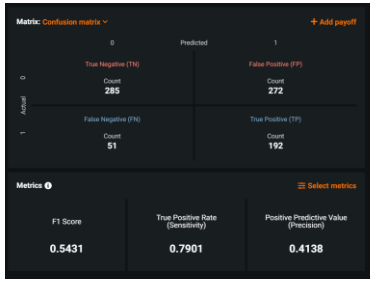
- Surgical pathways are an important element of HITH we've started flagging these patients in the tool prior to their admission
- This "countdown to admission" incorporates regular HITH processes into our tool meaning more time saved for clinicians



Doing — ED specific algorithm

- As information recorded in the Electronic Patient Journey Board has become more valuable to our HITH prediction algorithm we are seeing the score of ED patients suffer
- We've begun working on an algorithm specifically for ED patients that does not consider EPJB to ensure we're flagging patients as early as possible





Planning — Considering other @home services

- We're considering how this tool could help recruit patients for other @home services as we are already incidentally creating occasional referrals for these other services with the current screening

Planning — Assess tool again post process change

- We would expect to see a growth in HITH admissions driven by the use of this tool, post process changes we will reassess to ensure that our hypothesis is correct.

Review

Initial challenges in creating a predictive model	Successful model built of newly classified data	Turning our model into a tool and testing validity	New lessons learned in implementation of our tool
▪ Without an EMR structured clinical data is rare ▪ Historic bias against @home admissions works against future prediction	▪ Using expert clinical judgement alongside NLP proved successful ▪ Replicating real world results showed value	▪ The model is only useful if it's results are given to clinicians in timely manner ▪ Real world testing aligned with our successful experiments	▪ Without staff buy in a useful tool sits unused ▪ Change management is essential especially in the world of ML and AI

Key Takeaways

- AI can augment but not replace clinical decision-making
- AI can shoulder the burden of some manual work
- Partnering clinicians with Data Analysts builds symbiosis
- Care beyond the walls is constantly changing
- Staff buy in is critical

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Questions?