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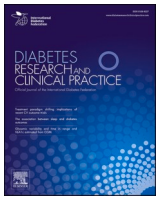

A pragmatic digital health informatics based approach for aiding clinical prioritisation and reducing backlog of care: A study in cohort of 4022 people with diabetes

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ABSTRACT

Background and aims: The backlog of care in resource stretched healthcare systems requires innovative approaches to aid clinical prioritisation. Our aim was to develop an informatics tool to identify and prioritise people with diabetes who are likely to deteriorate whilst awaiting an appointment to optimise clinical outcomes and resources.

Materials and methods: Using data from electronic health care records we identified 6 risk-factors that could be addressed in 4022 people (52% male, 30% non-Caucasian) with diabetes attending a large university hospital in London. The risk-factors were new clinical events/data occurring since their last routine clinic visit. To validate and compare data-led prioritisation tool to a traditional 'clinical approach' a sample of 450 patients were evaluated.

Results: Of the 4022 people, 549 (13.6%) were identified as having one or more risk events/factors. People with risk were more likely to be non-Caucasian and had greater socio-economic deprivation. Taking clinical prioritisation as the gold standard, informatics tool identified high risk patients with a sensitivity of 83% and lower risk patients with a specificity of 81%. An operational pilot pathway over 3 months using this approach demonstrated in 101 high risk people that 40% received interventions/care optimisation to prevent deterioration in health.

Conclusion: A pragmatic data-driven method identifies people with diabetes at highest need for clinical prioritisation within restricted resources. Health informatics systems such as our can enhance care and improve operational efficiency and better healthcare delivery for people with diabetes.

1. Introduction

There is a major backlog of care in resource stretched healthcare systems globally, related to the COVID-19 pandemic that resulted in non-emergency, scheduled hospital and specialist care being postponed in virtually all countries [1]. This disruption of routine care and the related backlog of outpatient appointments and waiting lists for many services requires urgent intervention to reduce clinical harm. Innovative data led systems have been proposed as a possible solution. [1] Indeed during the pandemic in surgical fields a standardised approach and framework was developed to enabled clinicians to target more accurately those patients with the greatest need and those who would see the greatest benefit [2].

Similar innovative data led approaches are also needed to effectively deal with backlog of care in ambulatory medicine. Diabetes is a long term condition that affects between 5 and 10% of the general population in many countries and globally the number of people with diabetes is increasing at a rapid rate [3]. It is also associated with a high burden of related complications often resulting in hospitalisation, premature morbidity and mortality [4,5]. Many of these acute and chronic complications can be delayed or prevented with prompt, effective intervention and enhanced care [5,6].

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Guy's and St Thomas' NHS Foundation Trust is a large university teaching hospital in London, that has more than 6000 people with diabetes in out-patient service follow up with ~ 80% of people under our care having Type 2 diabetes and ~ 1500 people with type 1 diabetes. During the COVID-19 pandemic, emergency in person diabetes clinics ran weekly but the majority of outpatient services were transformed to virtual clinics. As a consequence, there remains backlog of in person outpatient clinic visits and risk assessments pending with > 1200 follow up patients on the waiting list as of 2022.

In surgical specialities scoring-system based prioritisation approaches have provides a means to identify people who need prompt care and also as a means to reduce wait list times related to the COVID-19 pandemic [7]. However, to the best of our knowledge, no such systems has been designed nor evaluated in medical specialist services or the outpatient clinical care setting in the UK.

In specialist chronic disease outpatient services such as diabetes, clinicians frequently also do not have 'sight' of emergent or new risk between clinic appointments unless there is unscheduled /emergency care episode.

The aim of our proof of concept study was to use a framework of data driven criteria to enable an objective, standardised, informatics based system to aid clinical prioritisation in people with diabetes attending outpatient clinics in our hospital. Our clinical goal was to identify and prioritise people who are likely to deteriorate whilst awaiting an appointment, to minimise their risk and optimise clinical outcomes and resource utilisation.

2. Methods

We included all adult people (aged 18 and above) with diabetes attending Guy's and St Thomas Hospital awaiting diabetes follow-up clinic defined as future appointments in specialist led clinic. We excluded people in diabetes foot or podiatry services and diabetes pregnancy clinics.

2.1. Clinical risk criteria selection

We first evaluated a panel of risk criteria proposed by a national organisation for risk stratification in diabetes; these were raised HBA1c > 10% (>86 mmol/mol), uncontrolled hypertension (BP > 160/100 mmHg), complete Hypoglycaemia unawareness [Gold score > 4 if available [8]] or reported severe hypoglycaemia in the last 12 months, diabetes-related admission or unstable cardiac or cerebrovascular disease in the last 12 months, people recently discharged from hospital with changes in treatment, eGFR < 30 ml/min or rapid decline in renal function (>15 ml/min/year), and active diabetes-related foot disease [9]. These criteria were discussed within a group of 10 diabetes specialists who focussed on considered a pragmatic selection and consensus approach, with emphasis on modifiability of risk, accessibility of data/information currently available in the electronic health records data base and inclusion and exclusion criteria for the cohort. Following this review and discussion a list of risk criteria/flags with clinical parameters and criteria were agreed upon by the group (see Table 1).

The risk criteria selected by the group included three additional factors to those recommended nationally which were a low HbA1c risk criteria, HbA1c trends (rise and fall > 20 mmol/mol) as both may require prompt de-escalation /escalation of treatment promptly to mitigate hypo or hyperglycaemia risk and attendance for outpatient ophthalmology diabetes related retinopathy treatment (as often this may occur in our health care system autonomous to routine diabetes care and retinopathy progression can be modified with medical optimisation).

Our approach was based on using the above risk criteria in the scenario where the risk event was not known to the clinicians at the time of the person's last outpatient clinic attendance (i.e. all new risk events/flags were new events that occured after the person's last routine diabetes clinic review) and hence might reasonably be expected to change the assessment of cumulative modifiable risk at the point it became known. Our first goal was to embed this approach into a health informatics data and information framework to facilitate prioritization of clinical care to those with highest risk and therefore clinical need.

The longer term goal of this study is to use this foundation risk criteria and then add further criteria in the future, if this proof of concept was proven to be clinically valid on evaluation, informative, applicable to practice, and was able inform clinical service delivery.

Diabetes-related clinical and biochemical data, anonymised at source, was collected from electronic patient records for the cohort of people seen in our diabetes service since May 2020. The following variables were available including demographics (date of birth, gender, ethnicity which was self-reported), laboratory measurements (HbA1c and estimated glomerular filtration rate eGFR [10]. We also collated data from the ophthalmology clinical service with regard to their interventions /new treatment courses for advanced diabetes-related eye disease defined as a new photocoagulation, anti-vascular growth factor injectable treatment or retinopathy related surgery. Similarly, all hospital emergency room attendances or hospitalisation at Guy's and St Thomas with a diabetes-related cause (e.g. hyperglycaemia, hypoglycaemia, diabetes-related ketoacidosis, hyperosmolar hyperglycaemia) were collated for the data set. We measured socioeconomic status using Index of Multiple Deprivation (IMD). IMD are derived from UK Office for National Statistics tables and based on a participant's

Table 1
Diabetes clinical risk criteria utilised to guide data led clinical prioritisation in 4022 people with diabetes.

Criteria	Concerning High risk (red flag)	Ambiguous risk	Not Concerning Lower risk (green flag)
HbA1c - High Level	HbA1c > 86 mmol/mol	HbA1c in range 64–86 mmol/mol	HbA1c < 64 mmol/mol
HbA1c - Low Level	HbA1c < 48 mmol/mol		HbA1c >= 48 mmol/mol
HbA1c - Increasing Trend	Absolute increase* in HbA1c > 20 mmol/mol	Absolute increase* in HbA1c in range 5 – 20 mmol/mol	Absolute increase* in HbA1c < 5 mmol/mol
HbA1c - Decreasing Trend	Absolute decrease * in HbA1c > 20 mmol/mol	Absolute decrease * in HbA1c in range 5 – 20 mmol/mol	Absolute decrease* in HbA1c < 5 mmol/mol
eGFR - Decreasing Trend	Absolute* or annualised** decrease in eGFR of > 15 ml/min	Absolute* or annualised** decrease in eGFR of 5—15 ml/min (inc.)	Absolute* or annualised** decrease in eGFR of < 5 ml/min
Diabetes-related Hospitalisation or emergency room visit	One or more diabetes-related attendances since last consultation.	–	–
Diabetes-related Eye Disease Treatment (DEDT)	One or more DEDT procedures since last consultation where the series of treatments started after the last consultation	One or more DEDT procedures since last consultation where the series of treatments started before the last consultation	–

Abbreviations eGFR- estimated glomerular filtration rate, DEDT- Diabetes-related eye disease treatment.

* Absolute increase[decrease] calculated as difference between: minimum [maximum] of up to 3 most recent measurements in the 12 months prior to last consultation; and maximum[minimum] of any measurements after the last consultation.

** Annualised decrease calculated as maximum rate of change (scaled up to give annual rate of change) derived from pairwise comparison between: up to 3 most recent measurements in the 12 months prior to last consultation; and any measurements after the last consultation. Data median interquartile range or % shown.

postcode. IMD scores were ranked according to population deciles with these being labelled from one to ten with one indicating highest level of deprivation and ten being the most affluent [11].

This was a retrospective study conducted in line with local protocols using existing anonymized routine clinical data accessed directly by the teams and approved by hospital information and data governance committees and related data protection agreements.

2.2. Health informatics data led model scoring approach

The listed risk criteria in Table 1 were evaluated alongside data on all future clinical out-patient appointments within the diabetes service. Information and data that were ambiguous or encouraging are also detailed and listed on Table 1. Extracted data were pseudo-anonymised using a hash key and transformed into flat tables using Microsoft SQL Workbench. These data files were encrypted and securely transferred to Factor 50′s secure cloud-based servers within Microsoft Azure for further analysis. Data validation, clean-up, variable extraction and baseline statistical analysis was performed with Microsoft Excel and Microsoft SQL Workbench. All people were scored against the risk criteria using data that post-dated their last confirmed attendance in one of the consultant led clinics. Such data therefore represents information that was not known to the clinicians at the time of the person's last outpatient clinic attendance, and might reasonably be expected to change the assessment of modifiable risk at the point it became known.

Finally, by aggregating the outputs across all criteria (which were individually assessed as concerning, reassuring, or ambiguous based upon a given person's data) people were classified into groups as follows: high-risk (one or more concerning criteria); lower-risk (no concerning criteria, and one or more encouraging criteria); moderate-risk (no concerning or encouraging criteria, and one or more ambiguous criteria); and unknown risk (no new data since the last consultant-led appointment), please see Table 1.

Encouraging or lower risk were people who had new data since last clinic review that demonstrated stable improving clinical parameters with no evidence of deterioration and no high risk event. Similarly, moderate risk /ambiguous group were those who had new data but clinical parameters /results that were not at threshold to hit high risk -red flag criterion (please see Table 1 for detailed description). This person level risk segment was then selected as the final model output.

2.3. Clinical evaluation

In order to assess the degree of alignment between the health informatics data-led model and clinicians personal clinical judgment/ opinion a blinded validation of the prioritisation model was performed on a block subset of the data of 450 people with diabetes that ensured representative proportion of people with high and low risk indicators. The primary aim of this validation exercise was to ensure the sensitivity of the model to detect high risk people as compared to clinician's judgement. The validation cohort of 450 were divided in to groups of 60–70 people with diabetes and these groups were randomly allocated across seven clinicians who were asked to categorise the patients into high, medium, low risk or no new data) categories based on data available they could access in routine care (using electronic health records and test results for example as well elements of information not fed into the model). All clinicians were blinded to the model outcome. To maximise sample size with the available clinical resource, each case was initially reviewed by one clinician and the results collated and compared to the model outputs. In addition, when there was discordance between model and the clinicians judgment these individual cases were reviewed again by 5 diabetes specialists to obtain a consensus on the final risk category status.

All statistical analysis on this validation was thereafter performed using Microsoft Excel [12]. Specificity and Sensitivity of the health informatics data led model against clinical judgment were calculated for high and low risk patients and inter-observer variation was assessed with Cohen's kappa calculated for high and lower risk categories [12]. Data median interquartile range or % shown. No censoring was required due to the broad availability of follow-up data. Statistical tests were 2-tailed, with $P < 0.05$ considered significant.

3. Results

The baseline characteristics of our study population of 4022 people with diabetes (20% type 1 diabetes) are summarized in Table 2. Of the cohort 70% were Caucasians, with 30% of non-Caucasian heritage. Median and interquartile range (IQR), age was 52.3 (37.3, 63.8) years. We did not have complete information on smoking status or use of medications on the database. The median IMD decile of the cohort was 4 (IQR 2.3 to 5.8). The distribution of study population according to the different risk groups) is also shown in Table 2. Of the cohort 549 (13.6%) were categorised as high risk with a new 'risk' event occurring since their last routine clinical review/appointment. Similarly of the cohort 99 (2.5%) were classified as ambiguous, 2914 (72.5%) as had no new data since last clinic review) and 460 (11.4%) as (lower risk with reassuring/ stable new data since last review).

We observed that high risk people were more likely to be of non-Caucasian heritage (39.5% vs 30.2% p value < 0.01 (0.0034)) and also had a greater risk for emergency room /hospitalisation for diabetes-related cause (10.2% vs 4.8% % p value < 0.01 (0.0012). Similarly across all 4 risk groups those with highest new risk were more likely to be non-Caucasian, and have lower IMD scores indicative of greater socio-economic deprivation ($p < 0.05$ for trend) Table 2.

In the whole cohort the time gap in months between clinic appointments was 7.5 months for the whole cohort and this was broadly similar across all for four groups at baseline. We observed that there was little differentiation between the high-risk group, and the low-risk group (8.6 months versus 8.9 months between clinic appointments).

Of the 549 people identified in the high-risk group 243 (44%) did not have an appointment within 3 months of the data assessment date: 127 (23%) had an appointment booked>3 months away; 116 (21%) did not yet have an appointment booked at all. The remaining 306 (56%) of the high risk patients did have an appointment within 3 months (see Fig. 1 for more detailed breakdown).

Conversely, of the 460 patients within the low-risk group, 246 (53%) patients were due to be seen within the next three months and could potentially have their appointment deferred, while 137 (30%) had an appointment between 3 and 12 months away, and 77 (17%) did not have an appointment booked (please see Fig. 1).

The results of validation exercise compared the sensitivity and specificity of risk classification categories between the health informatics data led model versus clinical judgement/opinion of 7 diabetes specialists with a primary focus on accurate identification of those at highest risk. Of randomly selected 450 people or this blinded clinical evaluation of the data led model versus clinical judgement/opinion (which was set as the 'gold' standard). 350 had new data since the last consultation, i.e. were scored (high, ambiguous and lower risk), with the remaining 100 no new data. Of the 350 scored cases with new data in the full clinical assessment sample, 43 cases had to be discarded due to data not being correctly captured, or the protocol not being correctly followed. The majority of these were due to errors by the clinician in assessing what constituted new data. On the remaining 307 cases, and taking the clinician assessment as the gold standard, the health informatics data led model was found to have for high risk group a sensitivity of 84.8 ± 7.9% and specificity of 46.2 ± 8.1%, Lower risk group specificity was 80.6 ± 6.7% and sensitivity was 63.5 ± 7.2%. High risk Cohen's Kappa was 39.7% and lower risk Cohen's Kappa was 43.4%.

In order to ascertain whether discrepancies between the model and clinicians was due to clinical variation or model error, a senior diabetologists reviewed a sample of 67 cases in which the model and original clinician response did not agree. In 41 (61.2%) of these cases,

Table 2
Baseline characteristics and their distribution across the four risk groups classified by new risk criteria events post last clinic review in 4022 people with diabetes.

	Total N = 4022 (100%)	**New data High risk** N = 549 (13.6%)	**New data Ambiguous risk** N = 99 (2.5%)	**No new data** N = 2914 (72.5%)	**New data Lower risk** N = 460 (11.4%)
Non Caucasian	N = 1213 (30.2%)	N = 217 (5.4%, p=<0.01)	N = 47 (1.2%, p=<0.01)	N = 785 (19.5%, p=<0.01)	N = 164 (4.1%, p=<0.01)
Lowest IMD Deciles (1&2)	N = 753 (18.7%)	N = 124 (3.1%,p = 0.03)	N = 29 (0.7%,p = 0.01)	N = 511 (12.7%,p = 0.2)	N = 89 (2.2%,p=<0.01)
Age (Interpolation within 5 yr Bands)	Median = 52.3 (IQR 37.3 – 63.8)	Median = 55.3 (IQR 40.7 – 66.0) (p = NS)	Median = 58.3 (IQR 45.5 – 66.1) (p = NS)	Median = 51.0 (IQR 36.2 – 62.9) (p = NS)	Median = 55.4 (IQR 40.0 – 65.7) (p = NS)

Abbreviations Index of Multiple Deprivation (IMD) NS- non significant.
P values for trend between groups.

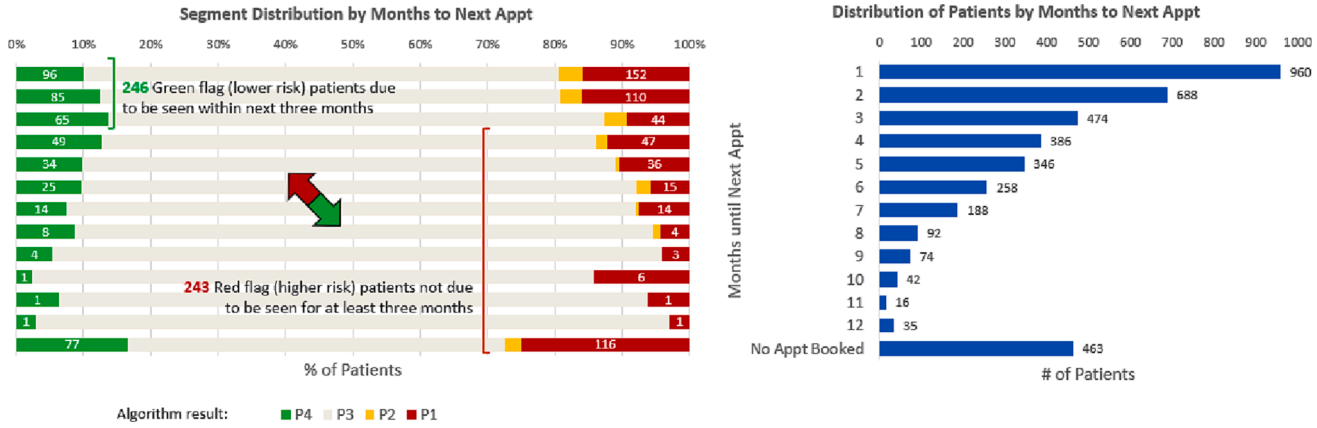

Fig. 1. Breakdown of people with new high risk events (red flag) and no new concerning data (lower risk- green flag) by next outpatient clinic appointment status demonstrating how this approach can decipher hidden risk and maximise clinical service efficiency to ensure those at highest new risk are prioritised.

the diabetologist agreed with the model outcome, and in only a single case (1.5%) did the model under-predict risk relative to the lead clinician, the rest (25, 37.3%) being where the model over-assessed risk relative to the diabetologist. To avoid any bias in the senior diabetologists assessments, 20 of these cases were also reviewed by a panel of 6 clinicians before arriving at a consensus view, and of these the consensus view agreed with the model in 13 of (65%) cases.

The pilot study also demonstrated time savings for clinicians to reach clinical decision as compared to current conventional approach using multiple information sources of data (electronic patient records and health data) with median time taken to perform clinical review to stratify risk/prioritise of 5.5 min with conventional approach versus 2 min using model.

We have also constructed a clinician facing dashboard that demonstrates an individual person's risk category (e.g. high risk) the relevant events and related clinical data and their wait time for next scheduled routine appointment (Fig. 2 and Fig. 3). This tool can be used by clinicians to inform their decision making and reduce unwarranted variation in clinical risk assessment. Similarly a bespoke clinic administrator dashboard to see appointment allocations according to risk and guide data led prioritisation of booking clinic appointments has been developed and implemented in practice (Fig. 4)

In a subsequent pilot project, we embarked on creating a high risk clinic to assess and intervene in a subset of 64 people identified by health informatics data led model with new high risk events since last clinic review but without a clinic appointment within 3 months. In this pilot clinic people have been evaluated by a multidisciplinary team of diabetes specialists 25 (~40%) people have had interventions/clinical care optimisation that will likely prevent deterioration in health or diabetes-related hospitalisation the most frequent intervention being interventions to reduce hypoglycaemic emergencies such as technology to monitor glucose, de-escalation of diabetes treatments, and self-management education.

4. Discussion

We have demonstrated in a data set of>4000 people with diabetes the feasibility of pragmatic data-driven health informatics model to identify people with diabetes at highest need for clinical prioritisation. As far as we are aware similar work in the outpatient setting has not been undertaken in diabetes or medical specialities. Of the cohort we studied 549 (13.6%) were identified as having one or more new clinical events/data occurring after their last routine diabetes clinic. We also observed that people with higher risk (P1) were more likely to be non-Caucasian with greater socio-economic deprivation. Moreover those at highest risk were also more likely to be hospitalised or attend emergency room for diabetes-related emergency.

In a subsequent validation exercise of 450 people with diabetes, taking clinicians opinion for risk categorisation prioritisation as the gold standard, we demonstrated that the health informatics data-led model identified high risk patients with a sensitivity of 83% and low risk patients with a specificity of 81%. Our proof of concept study utilised a pragmatic data-driven model to identify people with diabetes at highest need for clinical prioritisation. Such models have the capacity to identify

Patient Dashboard

Appointments	Date	Clinic Name	Clinic Code	Session Code
Last Seen	29/10/2021	Diabetes Clinic	DIAS-19	5UR
Next Seen	21/10/2022	Diabetes Clinic	DIAS-19	2EA

Overall Scores	Score	RedFlag	GreenFlag	NoData
	5	2	0	0

Criteria 1: A&E Visit since last seen	Outcome		
	1		
Criteria 2: HbA1c Level since last seen	Outcome	Result Used	
	No data	No data	
Criteria 3: HbA1c Change since last seen	Outcome	Difference	
	No data	No data	
Criteria 4: eGFR Level since last seen	Outcome	Result Used	
	Ambiguous	31	
Criteria 5: eGFR Change since last seen	Outcome	Difference	Rate
	Concerning	-21	-47.0
Criteria 6: DEDT Procedure since last seen	Outcome	Value Used (Diff)	
	0	0	

Fig. 2. Clinician and clinic administrator facing dashboards to guide prioritisation. Example of an individual person's risk category, related events, relevant clinical data and their wait time for next scheduled routine appointment. Fig. 2 Clinician facing patient dashboard. Fig. 3 Clinician facing patient dashboard with iindividual summary history chart to help with high level sense checking of the outcomes by presenting key data items on a timeline. Fig. 4 Clinic administrator facing dash board to guide data led clinical prioritisation for booking of follow up appointment.

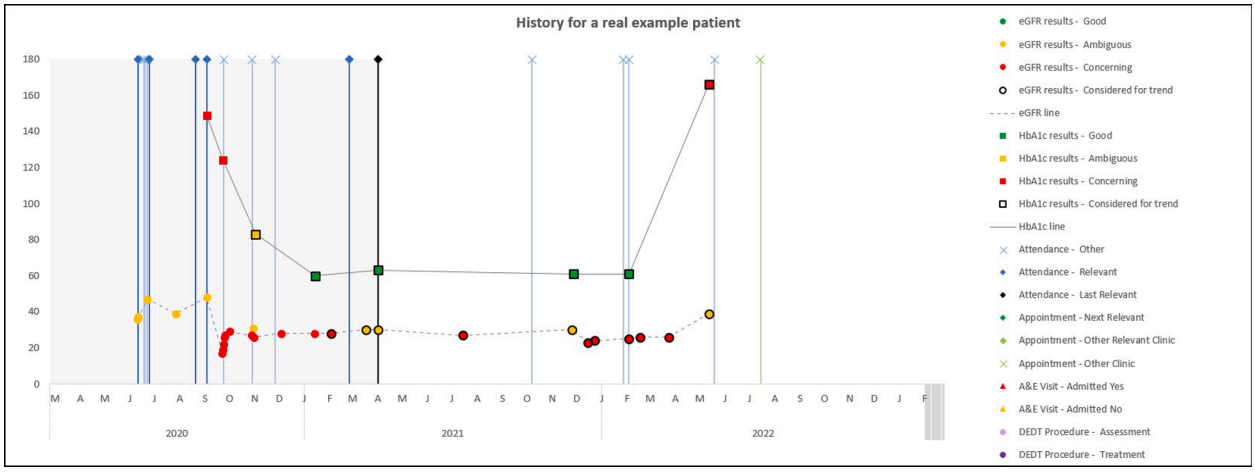

Fig. 3.

people who have deteriorated by virtue of having access to data that is not feasible or is too time consuming to obtain for clinicians in a time and resource scarce real-world clinical environment. Systematic reviews of patient prioritisation tools in non-emergency setting observed that the majority were for surgical interventions with implementation into clinical practice frequently lacking and a major challenge [7,13].

A further utility of such health informatics/data led models is their ability to automatically screen waiting list at intervals to identify new high risk people who require prioritisation of their appointments in a timely and efficient manner, reducing subjective assessment bias and variation in clinical assessments and preventing harm [2,7,14]. We hypothesise that approaches similar to ours can also lead to a decrease in wait times for people with diabetes most at risk of clinical deterioration, and prevent morbidity as demonstrated by similar tools used in elective surgery [15]. Further studies in similar long term conditions where there is regular outpatient care review are required to confirm our results.

From a real world perspective we have applied and implemented the model criteria and related findings to guide clinical appointment bookings in the setting of clinic cancellations due to unforeseen circumstances. In most large clinical services cancelled appointments are

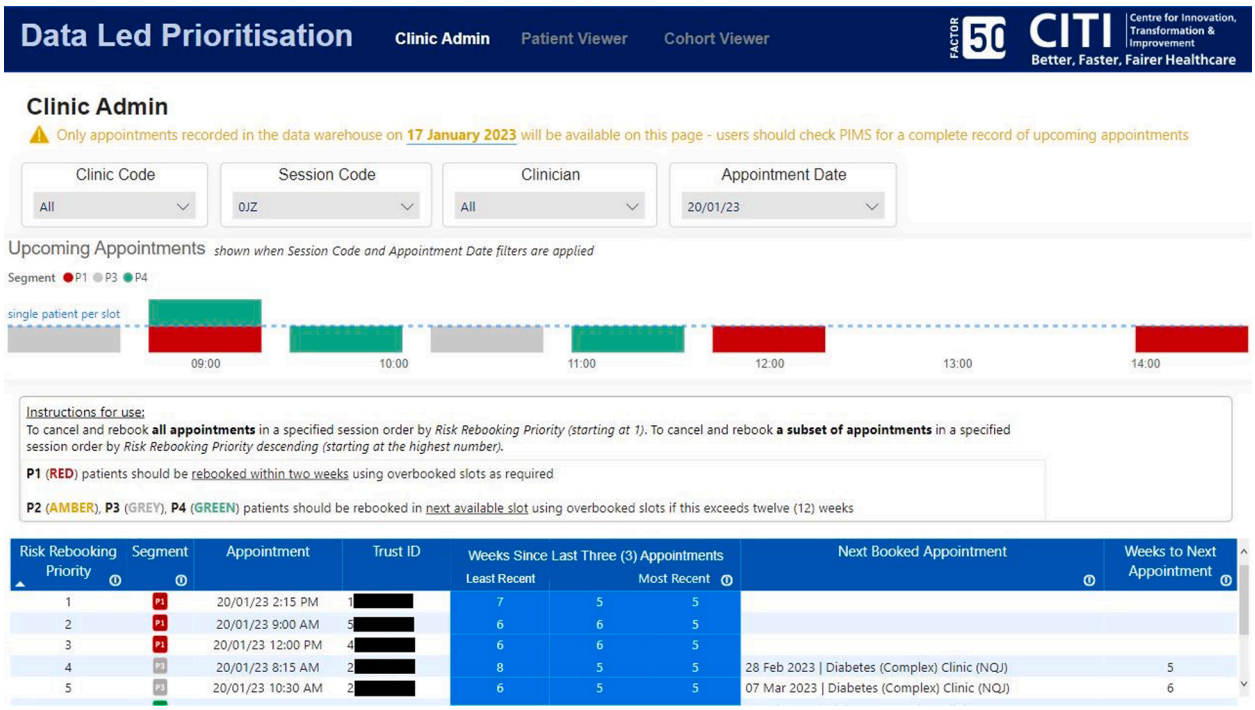

Fig. 4.

rebooked after individual review by senior clinicians or new appointments are booked by default without any prioritisation assessment of risk/new events, using a 'traditional' first in first out (FIFO) approach which often leads to longer waiting lists and potential clinical harm [13,16]. Our data driven model can facilitate appointment bookings to ensure those at highest need are prioritised first in this scenario and therefore could lead to improved health equity and efficiency.

The recent COVID-19 pandemic highlighted significant health inequalities and inequities in those from non-Caucasian and deprived communities facing a greater burden of disease [17–19]. This trend was confirmed in our study of people with diabetes attending outpatient services and suggests that objective data led process are required to proactively address this prevalent inequity contributing to disparate outcomes in those at highest clinical need and risk.

In our study we were able to demonstrate a high sensitivity for high-risk people and a high specificity for lower risk people, which suggests that similar data driven model can be used as a tool to safely identify people who may require less intensive follow up or be suitable for patient initiated follow up or remote review [20,21]. In this scenario we envisage being able to utilise these lower risk appointment slots to facilitate appointments in higher risk people with newer events, without creating additional workload or resource utilisation. This would ensure delivery of equitable prioritised care for those at highest need. Such patient initiated follow up approaches have been demonstrated to reduce waiting times, healthcare costs and improve service efficiency [22]. In our pilot study we were able to demonstrate that targeted high risk clinical service 40% of patients have had interventions/clinical care optimisation that have prevented deterioration in health or diabetes-related hospitalisation. The pragmatic digital health informatics prioritisation strategy we utilised enabled efficient handling of large sets of clinical data that would not be feasible by manual approach. Indeed manually prioritising of waiting lists to identify those most in need is impractical and likely to be inconsistent. Our approach identifies groups of people where we can potentially move appointments back in those who are at lower risk or have no new risk events thereby creating capacity to see those at highest need which enhances clinical pathways and service delivery in resource stretched systems, address health inequity and unmask hidden risk in waiting lists.

There are several limitations of our study. These include the selection of risk criteria which were based on clinical opinion of diabetes specialists albeit informed by national guidelines on risk criteria which, to a large extent, were included in our model. Our data set excluded people with diabetes-related foot disease or pregnancy, where often dynamic clinical changes occur at varying time frequencies, and hence our results cannot be applied to these clinical settings. Our urban cohort of people was having care in a tertiary care hospital, looking after people with complex diabetes, in an ethnically and economically diverse setting and hence our approaches and methods need to be applied and validated in other clinical and demographic environments. We set as gold standard clinician judgement on risk and compared our data led health informatics model to this assessment. We did not have the resources to have each case assessed by all clinicians to assess inter-clinician variability and find consensus categorisation to compare to model categorisation which would have been a more robust approach. As this was a proof of concept study it was not designed or powered to establish morbidity/mortality outcomes of people identified at high risk.

A further limitation of our study and other similar data led clinical prioritization approaches is the need for follow up studies to assess and evaluate the longer term impact of the methodology used. Such follow up studies are needed to confirm the longer term clinical and health economic impact of data led prioritisation approaches such as ours.

The strengths of our study include demonstrating the feasibility of a pragmatic approach to data led clinical prioritisation in a real world clinical setting. This work has been led and guided by clinicians and health informatics teams who are conscious of local health needs and available resources including administrative time to book and cancel appointments. We were able to demonstrate the value of a data led approach in>4000 people with diabetes and validated our model in a large subset with good sensitivity for identifying those at highest risk and need.

Our approach has been iterative and we have continually implemented our learning to practice. The value of this approach in our service has been proven in scenarios of unforeseen clinical cancellations where our model is used to ensure appropriate follow up, review of

people who do not attend to ensure those at new high risk are rebooked for review as a priority, and delivery of a targeted scheduled outpatient service for high risk patients. The lessons learnt and related informatics based approach used by the diabetes service are now being developed applied to other specialist medical services in our hospital who are developing similar models.

In conclusion our study demonstrates both the applicability and validity of a pragmatic data-led clinical prioritisation system in a large cohort of people with diabetes attending outpatient clinical services. Such automated health informatics system can identify people at highest need for clinical prioritisation, reduce the backlog of care more effectively in a data led manner, and can improved clinical service efficiency for people with diabetes and other similar long term conditions.

5. Contribution statement

JK, ST, DR conceptualised and designed the project as well as leading the clinical evaluation,data interpretation and providing clinical oversight. BM, MJ, CS provided programme management, data extraction, data interpretation, input to project iteration and lead project design which is aligned to the Trust's strategic objectives. AA provided data transfer and pseudonymisation between parties. OF, LN, AS aided with pilot study design, performed data synthesis, analysis and data interpretation. GB assisted in medical writing and data interpretation. JK, ST and DR wrote final paper and are guarantors of this work. All authors have reviewed the article and approved the final.

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Conflicts of interest

OF, GB, LN, AS are employed by Factor 50.

Declaration of Competing Interest

OF, GB, LN, AS are employed by Factor 50. All other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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