Memo

Briefing on the proposed governance of Algorithms in the Ministry of Health – COVID-19

Date:	15 February 2022
To:	Dr Ashley Bloomfield, Director-General of Health
Cc:	Shayne Hunter, Deputy Director-General, Data & Digital Bridget White, Deputy Chief Executive, COVID-19 Health System Response Caroline McElnay, Director of Public Health, Population Health and Protection
From:	Jon Herries, Group Manager, Emerging Health Technology & Innovation
For your:	Approval

Purpose

1. The Ministry of Health (the Ministry) is currently developing algorithms that are designed to improve the targeting of services and reduce the workload for clinical services in the Omicron response.
2. There is a need for the Ministry to implement and maintain governance of these algorithms to mitigate risks associated with algorithms and ensure we get the benefits from having them. It is important to note this is not a one-off process or limited to COVID-19 work and should consider the entire algorithm lifecycle.
3. This seeks approval for the formation and scope of this governance group and the membership of that group.

Background

4. As a part of the response to the Omicron outbreak, it is recognised that impacts on the health system will be outsized relative to previous outbreaks and variants, and more emphasis is being placed on self-management.
5. It has been proposed that a population level risk assessment would help local hubs understand the likelihood of high care needs and hospital admission. This would then help with prioritisation of cases to manage clinically and provide insights to local teams about the likely population impacts of high case numbers. It is also critical to ensure the resources are directed in an equitable way.
6. In order to implement an algorithm such as this, there are a number of best practice options for understanding the algorithm and providing authorisation for their use, management and review. These include guidance issued by Data & Digital, the National Ethics Committee framework, the clinical process in place in Waitemata District Health Board, the government's Algorithm Charter, and various international frameworks.

7. There are a number of key risks associated with the implementation of algorithms including:

   a. **Unintended consequences** – where the algorithm is developed and used and results in outcomes other (potentially worse) than would have occurred without using an algorithm. Often this relates to systemic bias in data or the use of data that is a poor substitute for an actual predictive feature. This could also be related to using an algorithm in an area that it isn't designed for. The consequence of this could be any type of risk depending on the algorithm including physical harm, financial liability, media and public confidence risk.

   b. **Models that are not performant** – where an algorithm is used that isn't successful enough or not as good as the existing process. The consequence of this can be abandonment of algorithms and poor outcomes for those affected or who can't access services that get withdrawn with the model. This could include increasing or perpetuating inequities. Often this has been avoided in healthcare as we usually have data driven performance standards that these would need to meet.

   c. **Model drift or lack of management** – when an algorithm is implemented it is being added to a process which continues to change and evolve. Without continuing to monitor the performance of the algorithm there is a risk the two issues identified above can occur.

8. In New Zealand, as a part of the Ministry of Business Innovation and Employment's (MBIE) Covid Innovation Acceleration Fund, an existing health sector investment received further funds to develop and deploy an algorithm hub. The organisation, Precision Driven Health (PDH) is a partnership founded by Orion Health and is charged with investing in data-driven research in health in New Zealand. The algorithm hub is where the mathematics of an algorithm are published along with an assessment of the benefits and risks and an ability for the public to see how it works and test it.

9. The outcomes from this process, the capacity and capability offered by PDH and availability of the hub are being used to provide the Ministry with expertise that is currently not available in house (or is unavailable due to capacity constraints). It is the governance approach tested by PDH over the past two years, with suitable modification, that we are proposing to use and this paper discusses.

10. The PDH team are further helping with a technical validation of the initial population risk algorithm and will be able to assist in managing algorithms on an ongoing basis.

Proposed Governance Model

11. A governance model for running and managing algorithms is best undertaken in a multi-disciplinary fashion. This means including expertise from communities affected by algorithms, experts in data, statistics, population health, clinical care, technology and business system design and implementation, ethics, legal and privacy perspectives. In New Zealand it is also best practice and a requirement to partner effectively with Māori to ensure that the outcomes of our activities reduce inequity and allow us to live up to the principles of the Treaty. Further the Ministry is a signatory to the Governments Algorithm Charter and it will be very difficult to discharge our responsibilities without a Group like this.

12. The process of approving the deployment of an algorithm and then making changes and managing model drift are important roles for the Governance Group as well as making decisions to withdraw an algorithm from production. A copy of the type of evaluation used by the Algorithm Hub is attached in Appendix One and describes the type of questions that should be answered before making an algorithm available.

13. Drawing from this and considering a more holistic role, the group is required to:
    a. Based on a written assessment completed about a model, provide expert advice in order to make good decisions on whether to put new algorithms into production and review material changes made to algorithms.
    b. Consider specifically the performance, likelihood of unintended consequences and monitoring steps required for algorithms in production.
    c. Advise on the process of developing, reviewing implementing and retiring algorithms.
    d. Recommend to the organisation (ie, business owner) whether an algorithm should be implemented, and provide suitable mitigations.
14. Assuming this is a useful approach (that may need to be adapted for Ministry use), there is then a need to consider who should be a part of a Governance Group to cover key aspects identified above. The table below shows existing members and other alternatives that could be considered for these roles in the first instance as it relates to our initial COVID-19 algorithm and in the immediate establishment of this function.

Role	**Algorithm Hub initial reference group**	**Initial COVID-19 Options**
Chair	Dr Kevin Ross	Ministry of Health, Dr Ashley Bloomfield or delegate. Bridget White Shayne Hunter Clinical lead (Chief Medical Officer, Chief Nursing Officer, Chief Allied Health Professions Officer)
Clinical	Dr Alex Kazemi	Dr Justine Lancaster (MoH) Dr Joe Bourne (MoH) Dr Pauline Horrill (MoH)
Public Health	Dr Juliet Rumball Smith[1]	Dr Caroline McElnay (MoH) Dr Robyn Whittaker
Māori impact	Dr Daniel Wilson	Andrew Sporle Dr Mataroria Lyndon Kiri-Kowhai Mikaere
Consumer Engagement	Dr Judy Blakey	Dame Diane Robertson
Data Science and statistics	Prof Gill Dobbie	Prof Thomas Lumley Prof Rhema Vaithianathan Prof Rod Jackson Dr Matthew Strother Te Pūnaha Matatini representative

[1] Note Juliet Rumball-Smith is an employee of the Ministry of Health and the Clinical Director for Precision Driven Health

Data	-	Simon Ross (MoH) Prof Colin Simpson Representative from VHIN eg, Laura Cleary (MoH) Could consider a person connected to the data sources (eg. a primary care person where Primary care data is used).
Ethics	Prof Tim Dare	Rochelle Style Nic Aagaard (MoH)
Legal & Privacy	Frith Tweedie	Phil Knipe (MoH) Fiona Wakefield (MoH) Could consider Office of the Privacy Commissioner in medium term
All of Government	Vince Galvin	May not be needed initially. Could consider research and other groups such as Disability or Pasifika.

15. It is expected that the composition of this group will change over time as the needs of the health system change and/or mature. The group should consider how their work will be used to establish a more permanent solution and whether/how this solution fits with the needs of the sector. This includes considering the changes to the role of the Ministry and Health NZ in operating operational algorithms.

Next steps

16. Subject to your approval of the need for a governance group and identifying members from this list (or others) the group will be able to consider and evaluate algorithms for development, deployment, and management in the first instance for COVID and then more widely.
17. Data & Digital will then work with PDH to establish Terms of Reference and the group. The costs of this work have already been accounted for in the short term in the Data & Digital COVID-19 work plan and funding.
18. The process of evaluation and the governance should be published along with the algorithm charter on the Ministry of Health website. The algorithms will be published to the algorithm hub.

Recommendations

19. It is recommended that you:

1.	note	Ministry of Health is developing a model and algorithm to support the Omicron response	
2.	note	Precision Driven Health has experience in the development and deployment of models and supporting the establishment of tools, processes, and governance relating to algorithms.	
3.	note	That Precision Driven Health will complete a technical assessment of this our initial model	

3.	agree	That a governance group is required to evaluate both technical and non-technical elements of an algorithm, to understand the intended and the likely outcomes of implementing them, and to endorse their use and management.	Yes/No
4	agree	The people who should be members of this group.	Yes/No

Signature _____ Date:

Dr Ashley Bloomfield
Te Tumu Whakarae mō te Hauora
Director-General of Health

Appendix 1 – Initial question set for algorithms to submit to the Governance Group

Algorithm_Information_Request_Templa

Appendix 2 - Links to key Documents relating to Algorithms, healthcare and governance

Document	Notes	Link	Date
D&D Using Algorithms in Healthcare	Describes potential issues and considerations when using algorithms in the New Zealand health system	Link	2019
Government Algorithm Charter	Describes commitment of the Ministry to the Government Algorithm Charter	Link.	2020
National Ethics Advisory Committee	Describes the NEAC guidance when developing new algorithms in a research context	Link	2019
A governance model for the application of AI in health care	Paper from Australia describing some key considerations in designing healthcare governance of algorithms	Link	Mar 2020

MINISTRY OF HEALTH
MANATŪ HAUORA

Memo

Supporting Our COVID-19 Affected Communities through a Population-Based Risk Stratification Tool

Date:	16 February 2022
To:	Ashley Bloomfield, Director-General
Cc:	Robyn Shearer - Deputy Chief Executive, Sector Support and Infrastructure Shayne Hunter – Deputy Director-General, Data & Digital
From:	Martin Chadwick, General Manager, COVID-19 Care in the Community
For your:	Approval

Purpose

1 The purpose of this memo is to seek approval to release the initial version of the COVID-19 population-based risk stratification tool, as part of the delivery of COVID-19 Care in the Community.

Summary

2 The COVID-19 Care in the Community team and the Data and Digital Directorate have developed a population-based risk stratification tool that will be part of the COVID-19 digital platform when a positive case is identified. The tool will support identification of people who should be prioritised for contact for the first clinical assessment which determines whether their COVID-19 care needs to be supported with active care management or the self-service pathway.

3 The tool is a simplified model using age, ethnicity and vaccination status data to inform risk of hospitalisation due to COVID-19. The team is working to include additional data sets that will strengthen the tools predictive capacity. An external peer review of the current model has been undertaken; it is included in Appendix A and B. This model has been validated. As we continue to develop the model, we will continue to undertake additional peer reviews to validate the model.

4 In its first iteration, the tool will support prioritising outreach from Care Coordination Hubs for those that do not respond to the initial text outreach from the national contact tracing solution (NCTS) system to indicate that they are positive for COVID-19. The rationale is that the majority of people notified that they have COVID-19 will follow instructions to complete self-assessment tools which will gather information around co-morbidities and other health

conditions that will provide more health information to guide pathway decision-making than the score can on its own.

5 There will be a portion of the population who do not respond to the initial prompt to complete self-assessment forms or cannot receive text message. For those people, the Care Coordination Hubs can use the risk score will to understand the individual's risk of hospitalisation and support prioritisation for outreach. Appendix C is a visual representation of the patient pathway.

6 At present, the Ministry of Health does not have a governance group to review the development, deployment and management of algorithms, such as this one. You will receive a separate memo proposing an approach, membership and mandate for an algorithm governance group. This will be important as this algorithm may be changed as we progress through the various phases of Omicron and possibly other variants.

Recommendations

It is recommended that you:

1.	**Note** the Ministry does not currently have governance for implementing algorithms into practice and this is in development.	**Noted** ✓
2.	**Note** that the algorithm has been technically reviewed, and there is a discussion of risks and mitigations described.	**Noted** ✓
3.	**Note** that there are opportunities to improve this tool and to use variants of it in additional places in the response.	**Noted** ✓
4.	**Approve** the COVID-19 Risk Stratification Tool for initial release with the planned mitigations in place. We will confirm the release date once the technology is ready for release and final business sign off has occurred. The hold up is due to finalising other, higher priority, technology releases.	**Yes/No** ✓

Signature _____ Date: 23/2/22

Dr Ashley Bloomfield
Te Tumu Whakarae mō te Hauora
Director General of Health

MINISTRY OF HEALTH
MANATŪ HAUORA

Supporting Our COVID-19 Affected Communities through a Population-Based Risk Stratification Tool

Background

7 This memo details the population-based risk stratification tool development, review process, and implementation plan. We are seeking approval to include the tool in the digital systems that are being developed to support people with COVID-19 in the community.

8 The Data & Digital Directorate and COVID-19 Care in the Community team have developed a population-based risk stratification tool that is derived from a model built by Waitematā DHB for assessing the risk of hospital admission for COVID-19 patients in the Northern Region.

9 This model was developed using cases from the Delta-strain outbreak over the past six months and using data available to the Northern Region from admissions, community services and primary care.

10 The primary use for the initial version of the tool is when a positive case is identified and does not respond to the initial text message alerting them of their status within 24 hours. The risk score will be used by Care Coordination Hubs to prioritise clinical outreach to non-compliant cases to determine if they will go in the self-service or active care management pathways.

11 Secondary use case of the tool will be to inform programme planning with the health sector as it relates to prioritisation of tests, therapeutics and workforce resources. The team is in the process of further developing this use case and will draft a memo for review prior to use.

Risk Stratification Tool Development

12 The tool sits in the COVID-19 Population Identification & Registration (CPIR) database. The tool provides a risk score between 0 and 1 that identifies whether a person is at higher risk of hospitalisation and in need of active care management or can manage their COVID-19 infection through the self-service pathway. A score closer to 0 indicates low risk of hospitalisation due to COVID-19, a score close to 1 indicates a high risk.

13 Precision Driven Health, through a contract with the Ministry of Health, has rebuilt the Waitematā model using data currently available through the Health Service Users (HSU) database: NHI, age, ethnicity, and vaccination status. However, since the model was originally developed there has been significant change - the dominant COVID-19 variant is now Omicron, vaccination rates have increased, age cohorts have expanded, and a booster programme is underway.

14 There is currently work underway to include prescribing data as a proxy for long term conditions in a future iteration of the model, and Waitematā is assessing other data that could be included, such as utilisation of mental health services. The team is working with the Data Architecture team to understand what data sets are available to use and appropriate with this work.

Risk Stratification Tool Review Process

15 We have endeavoured to undergo a rigorous review process to ensure that the tool is optimally developed, considered, implemented and used. Data & Digital has commissioned Precision Driven Health, an organisation specialising in data science (a subsidiary of Orion Health) to provide expert data science advice in the form of a peer review of the tool, advice on governance and access to their algorithm hub for publishing the mathematics of the tool once it is available.

16 We have presented and sought feedback from multiple groups around our methods and data sources including the Data Governance Group and the Health System Preparedness Program Advisory Group. The tool has been reviewed and supported by the Data and Digital Directorate, and the DHB Performance and Support Directorate. The COVID-19 Directorate has been made aware of the tool and its uses.

17 External communications to the health sector and general public are being developed to explain and clarify what the tool is and what it does. Messaging will be included in existing channels such as health key messages and sector webinars. Frequently Asked Questions will be developed to support both health sector and public communications and engagement.

18 Given the privacy considerations, the tool will not be actively promoted to the public; however information on how the tool fits into the wider care in the community strategy, and the role it plays in ensuring clinical and welfare support can be targeted to where it is needed the most, will be available on the Ministry website along with the privacy impact assessment, as per standard practice. A Privacy Impact Assessment is underway; thus far, the privacy advisor has indicated that the data and use of data meets the current rules and regulations.

Tool review, risks and mitigations

19 The tool has been developed to prioritise people who may need active management if they cannot receive a text or do not respond to the initial text message from NCTS upon receiving a positive diagnosis. It is under these parameters that the model needs to be measured against in how it has been designed, implemented and will be managed.

20 The benefits from the tool are likely to increase, as a rise in the number of cases requires the system to empower people at lower risk of serious outcomes from COVID-19 to self-manage. This enables the health system to focus resources on those who need active management, clinical care and support to isolate safely. The key risk with the tool is how good the model is at identifying those people who can safely undertake self-management (minimising those who can't self-manage being identified incorrectly as being able to self-manage). Appendix A includes a portion of the peer review undertaken by Precision Driven Health which articulates the capacity of the simplified model to achieve this.

21 The model is not perfect. In its current state, the model has limitations due to available data. Model limitations are due to the model being powered by data from the Delta outbreak (which is different from the current Omicron outbreak), and lower vaccination coverage from a time when eligibility was different for children and boosters were not yet happening. Summary statistics are included in Appendix B.

22 The current model likely underestimates the risk of hospitalisation by Māori and Pacific populations. This is in part because these groups represent small proportions of people hospitalised in the Delta outbreak, which informs the model. One way we can mitigate this is to develop specific models for Māori, Pacific and one for neither group to capture others.

23 There are risks that the algorithm as it is currently implemented could be perceived as not providing equitable outcomes. There are a number of mitigations that can be put in place. These include governance, adding additional data (e.g. booster doses, prescribing), controlling access to the outputs, further development of the mathematics (e.g. ethnicity stratified approaches). The mitigations are described in further detail below.

24 It is expected that additional data and further mathematical considerations would materially improve the quality of the tool. A critical question for consideration is when a tool is good enough to use (when the benefits outweigh the risks). Despite its limitations, we believe that using the tool in a limited scope (for people who do not respond to initial NCTS outreach as a part of multiple clinical inputs) is an appropriate use. As the model is strengthened with additional data, we will consider expanding its uses.

25 At this time, a number of mechanisms can be used to mitigate potential risks. These include:

- **Implement and ensure ongoing governance of the tool and other algorithms.** This would ensure that risk is assessed alongside benefit before use, and that the risk of unintended consequences can be monitored throughout the lifetime of the tool.
- **Limiting users.** We are looking at how we might expose this solution to a limited number of users in the Auckland region to gather feedback about how the score is shown, how it affects the clinical assessment process and to test messages about how it is being used.
- **Clear communication to the sector about what it can and can't be used for.** This will need to ensure that the health system doesn't use the model where it isn't suitable. The reality is that in its current form, many health professionals will be able to account for the variables in their clinical reasoning so will see little value. Contrastingly, we know that non-clinical users are likely to rely heavily on it and are likely to interpret it in a very black or white manner.
- **Putting a User Interface control in front of viewing the value.** We can limit access to who is using the tool and how they are using it in our initial deployment. This would help build confidence that the tool is being used appropriately and help guide us on how it can be improved.

26 With these mitigations in place, we can limit the number of users in order to gather feedback with the score and incorporate feedback into future versions.

27 The Ministry does not currently have active official governance of algorithms due to their current limited use and availability. This will change with the deployment of this tool and a separate memo has been prepared for approval to implement this.

Risk Stratification Tool Implementation

28 The risk stratification tool will be implemented as a part of the digital pathways being developed to manage the influx of COVID-19 cases; the tool will sit in the COVID-19 Population Identification & Registration (CPIR) database. When a person tests positive (or is identified as a close contact), their risk score will be pulled from CPIR into the National Contact Tracing Solution (NCTS) system and the COVID Clinical Coordination Module (CCCM).

29 The tool will be used to support prioritisation of the patient contact triage for COVID-19 cases that have not responded to the initial self-assessment forms from NCTS and need to be

clinically assessed. The score does not determine the services that a person will receive, as this is determined by their clinical and welfare assessment. Appendix C describes a person's process through the care journey and how this is determined.

30 As a part of determining who needs to be prioritised for outreach when a case has not completed the assessment form, the Care Coordination Hubs can use the risk score to determine who is at higher risk of hospitalisation, and prioritise contacting that person to undertake the initial assessment.

31 As noted above, the tool is iterative and will be updated as more data is reviewed and deemed appropriate to strengthen the model's predictive capacity. This may mean that people's scores will be updated over time. As the model is upgraded, the team will communicate the change in the tool and possible impacts to the Ministry and the health sector. The Ministry will ensure that as newer scores are generated, the original and previous scores will be available.

Equity

32 The purpose of the tool is to ensure equity by identifying and actively supporting those who are at high risk of negative outcomes due to COVID-19 by prioritising them for outreach to complete clinical assessments.

33 In using the tool, people at high risk of negative outcomes from COVID-19 such as Māori and Pacific people, will be identified early and supported directly through their local Care Coordination Hub.

34 As noted earlier, the tool is insufficiently powered to identify risk of hospitalisation based on ethnicity; this is a risk given how the model has been created that there are unintended consequences for Māori.

35 People who are not enrolled with a general practice will be picked up in a separate self-assessment and flagged as needing a health care provider assigned to support them.

Next steps

36 Upon your review and approval of the tool, we will complete the final deployment steps, with the intention of going live as soon as possible to begin testing the initial version.

ENDS

Appendix A: Summary from Technical Review by Precision Driven Health (PDH)

We do not believe that this model is sufficiently accurate at risk prediction to be used as the primary driver of treatment decisions. There appears to be a high likelihood that some people would be assessed as lower relative risk, but experience poor outcomes, therefore if this model is used then it should be done with significant and appropriate protections. We recommend that Governance consider an appropriate framework for deployment and display of this information. We do believe a suitable model could be developed using comorbidity or other information to improve accuracy. While the model development was technically sound, given the data constraints, overall risk estimation performance was average, with an AUC-ROC of 0.69 for the full data set. A range of statistical measures are used to report on how well the model estimates risk. We note that it is unclear what the status quo is in terms of risk estimation for the intended patient use cases, and therefore what the impact of the model would be should it incorrectly rank risk when used in practice. Informed by clinical judgement, there may be benefit in using the model for directing certain cohorts, e.g. very low-risk or very high-risk patients, to certain care pathways. It could also be used as a secondary input to a rules-based system to identify cases where the model considers a case to be high risk, despite being in a lower risk group according to rules. Considering the goal of explainability and current data constraints, we consider the feature engineering and model selection methods to be appropriate. We do note, however, that due to the timing of the data used for model development, this does not include boosters which will be relevant to Omicron management. Modelling does not capture days since vaccination/booster which could model declining immunity with time.

As we understand for reasons of current data availability at the national level, this model excludes comorbidities as explanatory variables. If such a model is to be developed and used for clinical decision support or autonomous patient triage during the Omicron outbreak, we recommend that all options are considered to enable the timely collection and accessible storage of data on health conditions at the national level.

Full Technical Peer review:

20220210 COVID-19 risk calculator - peer

Descriptive_data_profiling_V4.pdf

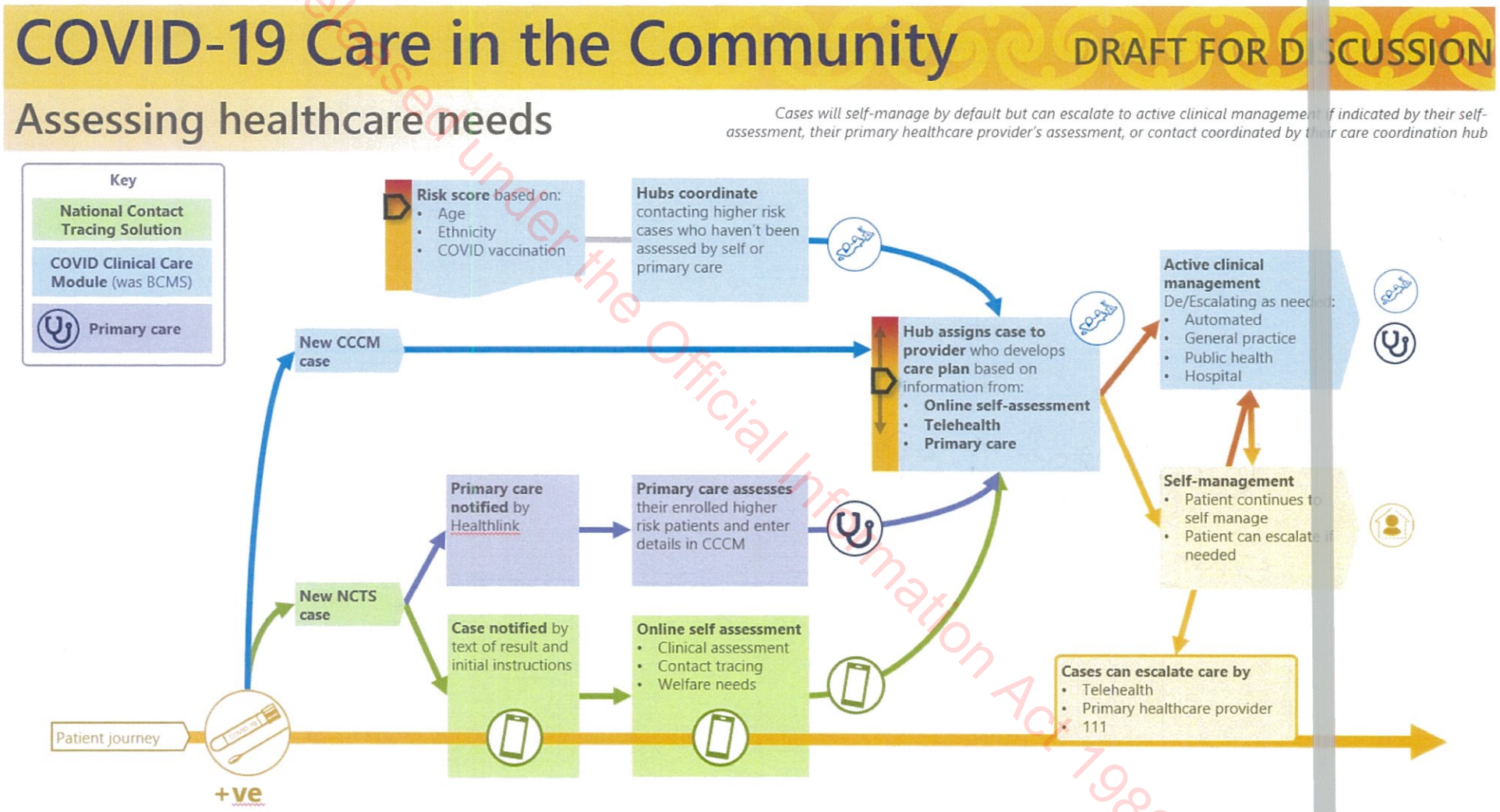
Appendix B: Summary Output Statistics, from Technical Review, PDH

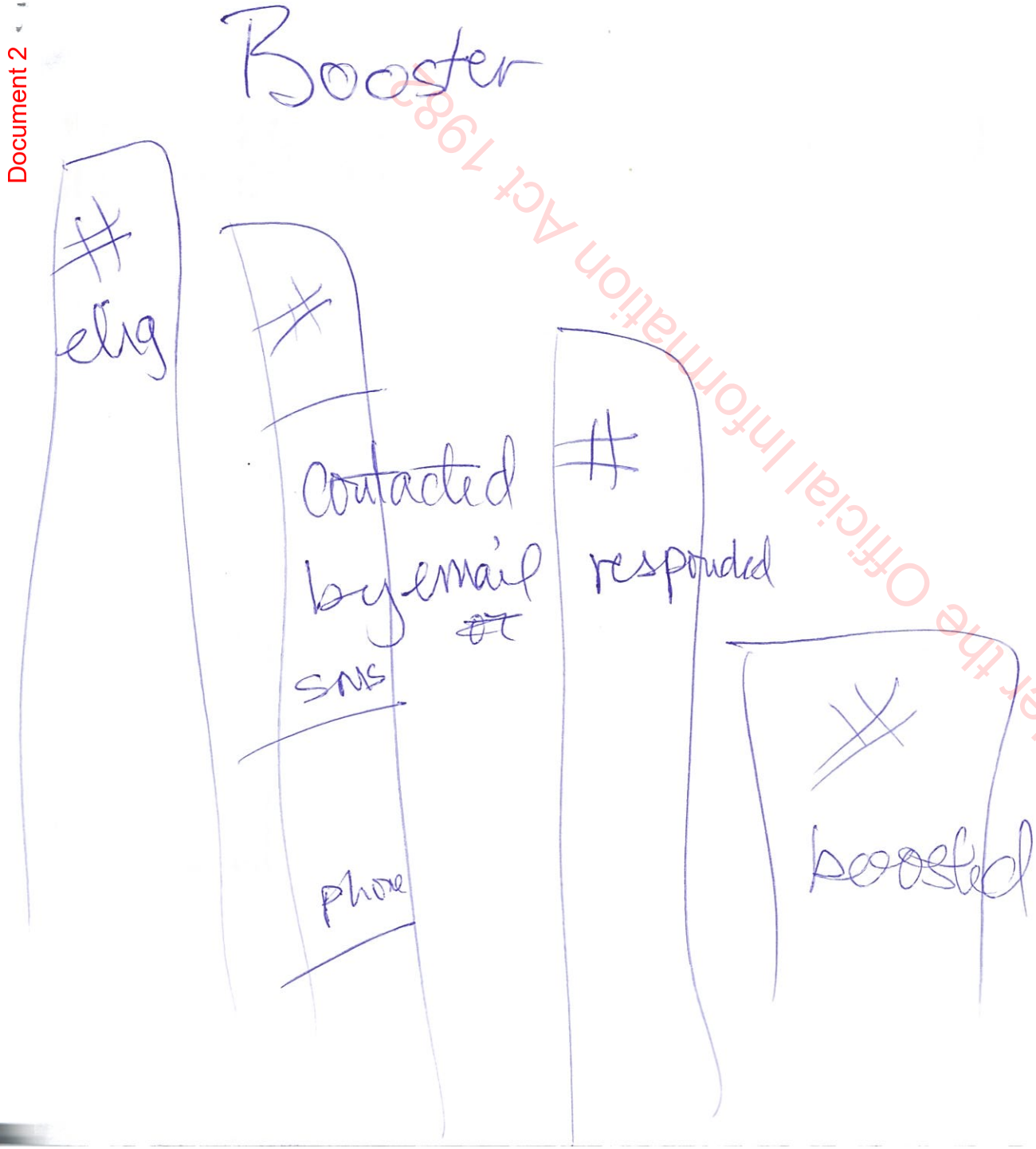
Confusion Matrix

	True	False	Total
Positive	**101**	**257**	**358**
Negative	**147**	**1170**	**1317**
Total	**248**	**1427**	**1675**

Sensitivity (True Positive Rate): 0.28 = TP / P
Specificity (True Negative Rate): 0.11 = TN / N
Accuracy: 0.14 = TP + TN / P+N
Positive Predictive Value: 0.28 = TP / TP + FP
Negative Predictive Value: 0.11 = TN / TN + FN

Appendix C: Patient Pathway and Risk Score





PRECISION DRIVEN HEALTH

COVID-19 risk calculator

DRAFT FOR DISCUSSION - IN CONFIDENCE

Peer review for Waitematā District Health Board and the Ministry of Health.

February 2022

DISCLAIMER

Precision Driven Health and Orion Health Limited do not warrant the accuracy, currency or completeness of any COVID-19 model and, to the full extent permitted by law, exclude all liability arising for any loss, damage or costs arising in connection with the COVID-19 modelling. By using the COVID-19 model you agree and accept that this is at your own risk.

MODEL VERSION 1.1, 11 FEBRUARY 2022

Model: Logistic regression, formula = target ~ age + maori + pasifika + Vaccination status

Data: COVID Dataset MoH V5.csv

Background

As New Zealand faces community transmission of COVID-19 and the Omicron variant, identifying patients at higher risk of poor outcomes is important to support an effective and equitable response strategy. Waitematā District Health Board (WDHB), through i3, has developed a predictive model for patients with COVID-19 at risk of deterioration using explanatory demographic and vaccination variables ("the simplified risk model"). Through the Precision Driven Health research partnership, a technical peer review of the simplified risk model has been requested.

The purpose of this document is to summarise the findings of the model peer review process.

PRECISION DRIVEN HEALTH

Scope of technical peer review

This review examines the methodology, assumptions, performance and suitability of the simplified risk model. Appendix A documents the reproducibility of the model in the context of the input data shared from WDHB.

Summary

We do not believe that this model is sufficiently accurate at risk prediction to be used as the primary driver of treatment decisions. There appears to be a high likelihood that some people would be assessed as lower relative risk, but experience poor outcomes, therefore if this model is used then it should be done with significant and appropriate protections. We recommend that Governance consider an appropriate framework for deployment and display of this information. We do believe a suitable model could be developed using comorbidity or other information to improve accuracy.

While the model development was technically sound, given the data constraints, overall risk estimation performance was average, with an AUC-ROC of 0.7 for the full data set[1]. A range of statistical measures are used to report on how well the model estimates risk (see Appendix A).

We note that it is unclear what the status quo is in terms of risk estimation for the intended patient use cases and therefore what the impact of the model would be should it incorrectly rank risk when used in practice. Informed by clinical judgement, there may be benefit in using the model for directing certain cohorts, e.g. very low risk or very high risk patients, to certain care pathways. It could also be used as a secondary input to a rules-based system to identify cases where the model considers a case to be high risk, despite being in a lower risk group according to rules.

[1] AUC-ROC is a measure that indicates how good the model is at ranking people based on risk. 0.5 indicates that the model is no better than random assignment to high risk/low risk and 1 indicates a perfect model. Slightly worse model performance was achieved for Māori people only and improved model performance (vs. full data set) for Pacific people only. The statistical literature generally describes an AUC-ROC between 0.6 and 0.7 as 'poor' or 'average' and 0.7 - 0.8 as acceptable (for example, Hosmer & Lemeshow (2013). Applied logistic regression. p.177)

Considering the goal of explainability and current data constraints, we consider the feature engineering and model selection methods to be appropriate. We do note, however, that due to the timing of the data used for model development, this does not include boosters which will be relevant to Omicron management. Modelling does not capture days since vaccination/booster which could model declining immunity with time.

As we understand for reasons of current data availability at the national level, this model excludes comorbidities as explanatory variables. If such a model is to be developed and used for clinical decision support or autonomous patient triage during the Omicron outbreak, we recommend that all options are considered to enable the timely collection and accessible storage of data on health conditions at the national level.

Model Development

Context

The Northern Region Health Coordination Centre requested that WDHB develop a model to predict risk of hospitalisation following a positive COVID-19 test. The model was to be trained on data from the Auckland region, then integrated into a COVID-19 Qlik dashboard.

Once deployed, the model would be used for patient contact triage.

In December 2021 WDHB developed a model exploring demographic, vaccination, comorbidity, medication, mental health and height and weight as explanatory variables ("the larger risk model"). Additional to the data sources for the simplified risk model (described below), this model included comorbidity and other data from community referral forms, community dispensary, and mental health data from Health Care Community.

The Ministry of Health later requested that WDHB develop a simplified risk model that could be used nationally, using only demographic and vaccination explanatory variables. This modelling was completed in January 2022.

While the simplified risk model is the subject of this review, the larger risk model provides a useful comparison for model performance with the inclusion of comorbidity information.

Requirements

- The Ministry of Health has required that model inputs be pared back to readily available variables, excluding comorbidities.
- The model must be explainable.
- The model outputs must be appropriate for patient contact triage.

Data sources

- Auckland Regional Public Health Service data feed - for COVID-19 positive patients in the Auckland region, extracted via COVID-19 Qlik Sense,
- Auckland regional hospital admissions database.

Confirmed and probable COVID-19 cases from the start of the Delta outbreak were included in the dataset. The time period covered was 19.08.21 - 29.11.21.

Comment

- *We note that a model trained in Delta outbreak data may not be appropriate for patient triage for the Omicron outbreak. We understand that the simplified risk model is to be retrained as Omicron data becomes available.*

Data acquisition

It is recommended that a process is put in place for reviewing the data acquisition process (including SQL scripts) used to derive the modelling data set. Ensuring that this has been reviewed and signed off early avoids later iterations of data refinement that impact the modelling.

Variables

As indicated by the Ministry of Health, potential explanatory variables were limited to readily accessible variables at the national level:

- Admissions to hospital due to COVID-19, using the 'COVID flag' for patients not cleared by public health.
- Community deaths
- Age
- Ethnicity
- Gender

- Vaccination status
- Deprivation quintile
- GP enrolment

Comment

- *The omission of comorbidities is not best practice for a COVID-19 risk model, as noted in the Risks and limitations section.*
- *A model that omits important variables that explain variation in the target variable can be used for prediction (with reduced performance), but not for understanding effects.*

Data pre-processing

Data exclusions

- **Specialty** - Admissions to maternity, ophthalmology, gynaecology, urology, ENT, adult acute mental health, substance abuse and orthopaedic, vascular cardiothoracic, general and specialist paediatric surgery services;
- **Facility** - Admissions to Auckland Mental Health Services, Taiho Mai (adult mental health), and Greenlane Clinical Centre
- **Age** - Patients under 12 years of age (vaccination exclusion)

After exclusions, 5,931 patients were included in the data used for modelling.

Missing data

No data was missing, therefore imputation was not required.

Balance

The dataset was imbalanced (14% in the target group).

Comment

- *The omission of chosen specialties and facilities is considered a clinical judgement and out of scope of this review.*
- *We do not consider dataset rebalancing necessary at this level of imbalance.*

Feature engineering

- **Clinical deterioration (Target)** - A binary variable set by the combination of admissions to hospital due to COVID-19 and community deaths.
- **Age** - no feature engineering for age evident in script provided.
- **Ethnicity** - five binary variables created: *Māori*, *Pasifika*, *European*, *Asian*, *Other*. This represents prioritised ethnicity with only one value recorded for each person in the data set.
- **Gender** - one binary variable created: *Male*
- **Vaccination** - two binary variables created: *Unvaccinated* and *One dose.*
- **GP enrolment** - one binary variable created: *GP* (enrolled = 1)
- **Deprivation quintile** - two variables explored in the model, raw quintile and binary variable *Low Deprivation Quintile*, (quintile <3 = 1)

Comment

- *Due to the timing of the data used for model development, this does not include boosters which will be relevant to Omicron management. We also note that the modelling does not capture days since vaccination/booster which could model declining immunity with time.*
- *The suitability of hospitalisation due to COVID-19 and community deaths as proxies for clinical deterioration is considered a clinical judgement and out of scope of this review. We do, however, note that there would be a higher level of intervention and care with small case numbers and without capacity constraints. There may have been precautionary hospitalisation during previous outbreaks that could bias the data used for model development.*
- *We note that cause of death assumes death from COVID-19 as opposed to death with COVID-19. We trust this assumption has been validated as there are known challenges with cause of death.*
- *Variables were appropriately converted into machine readable inputs.*

- *The degree of feature engineering is appropriate for a model that must be explainable, however we note that* Age *skewed young and* Deprivation Quintile *skewed high. A transformation of these variables could be explored (if not already).*
- *Collinearity between explanatory variables is acceptable.*
- *We understand that interaction terms were tried in the model exploration phase, and were not found to be significant at the time, however this work was not included in the simplified risk model documentation. Interaction terms describe how the impact of one explanatory variable on the outcome changes in terms of another explanatory variable. These terms can explain significant variation in the outcome. For instance, being aged over 65 and Māori could have a greater impact than the sum of the two independent variable effects. We would recommend further exploration, or documentation of prior exploration, of including interaction effects in the model.*
- *Consider exploring fine tuning the proxies of the deterioration as ordered classes and custom loss function to weight different types of errors. For example, a misclassification of a deceased case as requiring general hospitalisation is more wrong than a misclassification of this case as requiring ICU service.*

Choice of model

A logistic regression model was chosen for the ease of explainability. No other model was tried.

An initial model included *Age*, *Māori*, *Pasifika*, *Unvaccinated*, *One Dose*, *GP*, and *Deprivation Quintile*. *GP* and *Deprivation Quintile* were not significant and were excluded in the final model.

Comment

- *A logistic regression model is appropriate where explainability is important. Further because a logistic regression model outputs risk scores, patients can be ranked for triage. If used as a classifier (will/won't deteriorate) a threshold can be set to optimise a desired metric (e.g. to minimise false negatives).*

- *If the model is to be implemented as a risk calculator, a logistic regression model allows parameters to be set in a way that cannot be achieved with other, more complex, models.*
- *The trade off for explainability is that a logistic regression model assumes a linear relationship between the target and explanatory variables. If that underlying relationship is non-linear, model performance will be sub-optimal.*
- *It may be useful to rule out choice of model as a contributor to average performance by exploring other, less explainable models, in particular those that allow for non-linear decision boundaries (e.g. Decision Tree, Neural Network, K-Nearest Neighbours).*
- *It is not clear how variables were excluded for the simplified risk model. Stepwise regression is assumed, however a lasso method is an alternative. We note that in the presence of comorbidities, it is possible that one or more of the excluded variables could explain residual variation.*

Assumptions

- Undetected cases not in scope
- Patients with the 'COVID flag' and included in the data set were admitted to hospital because of COVID-19.
- Cause of death is COVID-19.

Tuning

The model was trained and evaluated using COVID-19 cases in the Auckland metro area. It has not been tuned towards other populations or any particular ethnicity groups. There is a risk of bias in the model towards reflecting the Auckland metro population (in ways that are not adjusted for by the variables in the model) and the healthcare settings in this region.

Train/test

The data set was split into 80/20 partitions.

Comment

- *We note in the R-script provided, 10-fold cross validation was also used to evaluate model performance. This is standard and*

metrics based on this testing would be appropriate, however were not provided.

- *We recommend that both model selection and training be revisited as Omicron data becomes available.*
- *Be cautious of concept drift while revisiting the modelling, especially the standard of hospitalisation might change as Omicron cases increase.*

Performance metrics

The area under the receiver operating characteristic curve (AUC-ROC) was the main performance metric used for model training. Calibration graphs were displayed for the test set and the entire dataset, as well as for the ethnicity-specific entire datasets (Māori and Pasifika). No other performance metrics were reported.

Performance of the model showed average discrimination as assessed by the model developer (AUC-ROC 0.7). For context, AUC-ROC of 0.5 is no better than a random guess, and AUC-ROC of 0.9 or above is excellent.

Comment

- *The documentation provided for the simplified risk model implied that this was performance on the training set. If so, we would expect lower performance on the test set.*
- *We consider there are significant risks associated with the use of the simplified risk model without further analysis. While the model development was technically sound, given the data constraints, overall performance was average. We note that it is unclear what the status quo is for patient triage and therefore what the impact of the model would be should it incorrectly rank risk. Informed by clinical judgement, there may be benefit in using the model for directing certain cohorts, e.g. very low risk or very high risk patients, to certain care pathways.*

Documentation

Comprehensive documentation was provided for both the simplified risk model and the larger risk model. According to the model developer, the larger risk model was documented to the TRIPOD standard.

Risks and limitations

Comorbidities are not included in the model

National and international guidelines advise that patients with certain medical conditions are at higher risk of becoming severely ill from COVID-19 (MoH, 2022; WHO, 2022; CDC, 2021; NHS, 2022).

The larger risk model developed by WDHB demonstrated within the population of interest that comorbidities were important predictors of clinical deterioration. The absence of these predictors in the model limits performance, application and interpretation of effects (as ethnicity and age likely become proxies for comorbidities).

We note that other models such as the 4C Deterioration score developed by the ISARIC consortium also include information about a patient's comorbidities when estimating risk (https://isaric4c.net/risk/).

There are risks with generating predictions about outcomes for cohorts of people that do not adequately incorporate information about existing health conditions. Māori and Pacific people in New Zealand have a greater burden of disease due to structural inequities. McLeod et al. (2020) in their commentary 'COVID-19: we must not forget about Indigenous health and equity' highlight differences in multimorbidity between Māori and non-Māori and link this with the risk of poor outcomes from COVID-19.

Inclusion of ethnicity as a variable

The use of ethnicity as a variable within predictive models is complex and multifaceted, as is the capture and use of ethnicity information (Harris et al., 2013). This topic is beyond the scope of this technical peer review, and we trust that appropriate guidance from Māori health experts has supported the inclusion of ethnicity as a predictor in this model. We note that prioritised ethnicity is being included which does not account for people with multiple ethnicities.

Māori and Pasifika impact

The model has not been tested for validity for Māori or Pasifika ethnic groups (with AUC-ROC). We recommend that stratified performance results be produced per ethnicity and checked.

We also note that an age and ethnicity interaction term is not included in the model. Without such a term, the model may be downweighting the effect of ethnicity which may impact predictions for all ethnicities.

Suitability of New Zealand data used for modelling

While the model will help to adjust for certain variables, the input data may not be representative of COVID-19 patients in the future, therefore the model may not generalise well when deployed nationally:

- The training data used may be biased towards a cohort who are primarily young and healthy, and who are able to travel and return to New Zealand.
- We understand that in the August 2021 outbreak, Māori and Pacific cases were younger than the population average for those cohorts.
- There would be a higher level of intervention and care with small case numbers. In the Delta outbreak we understand that there was precautionary hospitalisation that may not occur in a widespread Omicron outbreak. This highlights possible issues with using hospitalisation as a proxy for clinical deterioration.
- Different COVID-19 variants present different risks for clinical deterioration.
- Vaccination induced immunity declines over time and boosters may need to be included in future models.

Use and calibration of the model outside the Northern region

We understand that this model is proposed to be translated to a national setting.

This Algorithm Information Request template used by the New Zealand Algorithm Hub governance process is attached as a reference and guide for deployment and governance. This document outlines considerations for model purpose, development, deployment and management, Māori impact, equity, legal and risk, and ethics.

Recommendations

Item	Recommendation
Data acquisition	• Develop a process for reviewing the data acquisition process (including SQL scripts) used to derive the modelling data set. Ensuring that this has been reviewed and signed off early avoids later iterations of data refinement that impact the modelling.
Model Selection and training	• Revisit model selection and training as Omicron data becomes available. • Explore the inclusion of interaction terms in the simplified risk model, in particular Age and Ethnicity. • Be cautious of concept drift while revisiting the modelling, especially the standard of hospitalisation might change as Omicron cases increase. • Explore fine tuning the proxies of the deterioration as ordered classes and custom loss function to weight different types of errors. For example, a misclassification of a deceased case as requiring general hospitalisation is more wrong than a misclassification of this case as requiring ICU service.
Model evaluation	• Analyse the performance of the simplified risk model per ethnicity. • Document model performance via 10-fold cross validation.
Model deployment	• Review the risks and benefits of the model in the context of proposed use cases to understand how the simplified risk model could be safely used.
Model governance	• Please refer to the attached AIR as a guide.

References

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- World Health Organisation (WHO). (2022). *COVID-19: vulnerable and high risk groups*. Retrieved January 27, 2022, from https://www.who.int/westernpacific/emergencies/covid-19/information/high-risk-groups

PRECISION DRIVEN HEALTH

Appendix A

Note that the data related reviews were undertaken with the dataset provided. This dataset contained 664 covid cases dating from before the Delta outbreak, 416 of which were in the filtered dataset used for modelling. The results included below are therefore indicative only, pending refreshed data.

Reproducibility

Component	Reproducible	Comments
R script runs successfully without errors	Yes	We recommend established code templates to facilitate collaboration going forward.
Rationale/approach to variable selection is clear	Yes	
Model intercept	Yes	
Model coefficients	Yes	
P-values	Yes	
AUC (full model)	Yes	

Data preparation

Variable	Preparation	Comments
Sampling strategy	Removal/selection of duplicate patient records Oversampling if required for a rare outcome	Handling of duplicates cannot be assessed with data provided, however duplicates were removed from the dataset. The dataset was

		imbalanced but oversampling is likely unnecessary not necessary
Information leakage	Any future data leakage e.g. data that reflects a hospital admission?	It is possible that some of the same patients that are used in this training data set will be risk stratified in future, however after removing duplicates, test and training data should be separate for future model updates.
Correct loading of variable types (numercial, categorical etc.)		Variable types were handled appropriately in the R code.
Exclusion criteria	Non-confirmed COVID cases (COVID_Status = -) Age under 18	Logic implemented correctly
Ethnicity	maori = c('M?ori') pasifika = c('Samoan','Tongan','Cook Island M?ori','Niuean','Other Pacific peoples','Fijian','Tokelauan','Pacific peoples NFD') european = c('New Zealand European','Other European','European NFD') asian = c('Indian','Southeast Asian','Other Asian','Chinese','Asian NFD') other = c('Middle Eastern','African (or cultural group of African origin)','Latin	All ethnicities were captured by the flags created. Note that the apostrophe in 'Don't know" has been represented in more than one way in the datasets provided and care should be taken with filtering to that value. Only Pasifika and

	American/Hispanic','Not stated', 'Response unidentifiable','Other ethnicity','Don't know')	Māori flags were used in the model.
Age	No transformation	Age was skewed and we understand that an age transformation will be explored with interaction terms with Ethnicity.
Target	Hospital Admission = 1 OR Death = 1	Source of hospital admission and death fields is unclear. Assuming these are correct, logic implemented correctly.

Data Profiling

Descriptive data profiling was run over the *COVID Dataset MoH V5.csv* to assist visual examination of the features in the dataset and initial checking of their relationship with the target values.

The visualisation covers:

- Distribution of the feature values
- Feature distribution change along time ('Reported_Result_date') - weekly aggregated feature value counts
- Proportion of different target values in each feature value group - potential association between the feature and the target

Chi-square test was applied to statistically examine the significance of association for the following:

- Missingness vs. target (hospital admission)
- Binned numerical feature values vs. target (hospital admission and death respectively)
- Categories vs. target (hospital admission and death respectively)

A conventional significance level of 0.05 was applied. For significant associations, a Cramér's V coefficient was calculated to indicate the strength of the association (0: the weakest, 1: the strongest).

Following initial review of these profiling outputs, there is no particularly strong predictor for the target on its own in this dataset.

The ethnicity-stratified profiling for 'age' indicates that the relationship between age and target is inconsistent among different ethnicity groups which might indicate the inclusion of an interaction term in the model.

No particular concerns regarding data distribution or data quality were identified through this profiling.

Performance metrics

AIC: 4014.2

Precision, recall and F1-score are based on a threshold of 0.15 across all groups and are an average of 10-fold cross validation.

The confusion matrix is based on a 70/30 random training/test split of the data. Numbers in the matrix are from the test set.

Cohort	**ALL (10-fold CV average)**
AUC-ROC	0.70
Precision	0.24
Recall	0.63
F1-Score	0.35

Confusion matrix ALL

Hospital/Death		Actual	
		TRUE	FALSE
Predicted	TRUE	95	224
	FALSE	138	1099

Cohort	**Māori (10-fold CV average)**
AUC-ROC	0.69
Precision	0.24
Recall	0.61
F1-Score	0.34

Confusion matrix MĀORI

Hospital/Death		Actual	
		TRUE	FALSE
Predicted	TRUE	30	89
	FALSE	57	418

Cohort	**Pasifika (10-fold CV average)**

AUC-ROC	0.72
Precision	0.27
Recall	0.73
F1-Score	0.39

Confusion matrix PASIFIKA

Hospital/Death		Actual	
		TRUE	FALSE
Predicted	TRUE	42	77
	FALSE	45	340

Cohort	**Not Māori or Pasifika (10-fold CV average)**
AUC-ROC	0.67
Precision	0.22
Recall	0.51
F1-Score	0.30

Confusion matrix, NOT MĀORI OR PASIFIKA

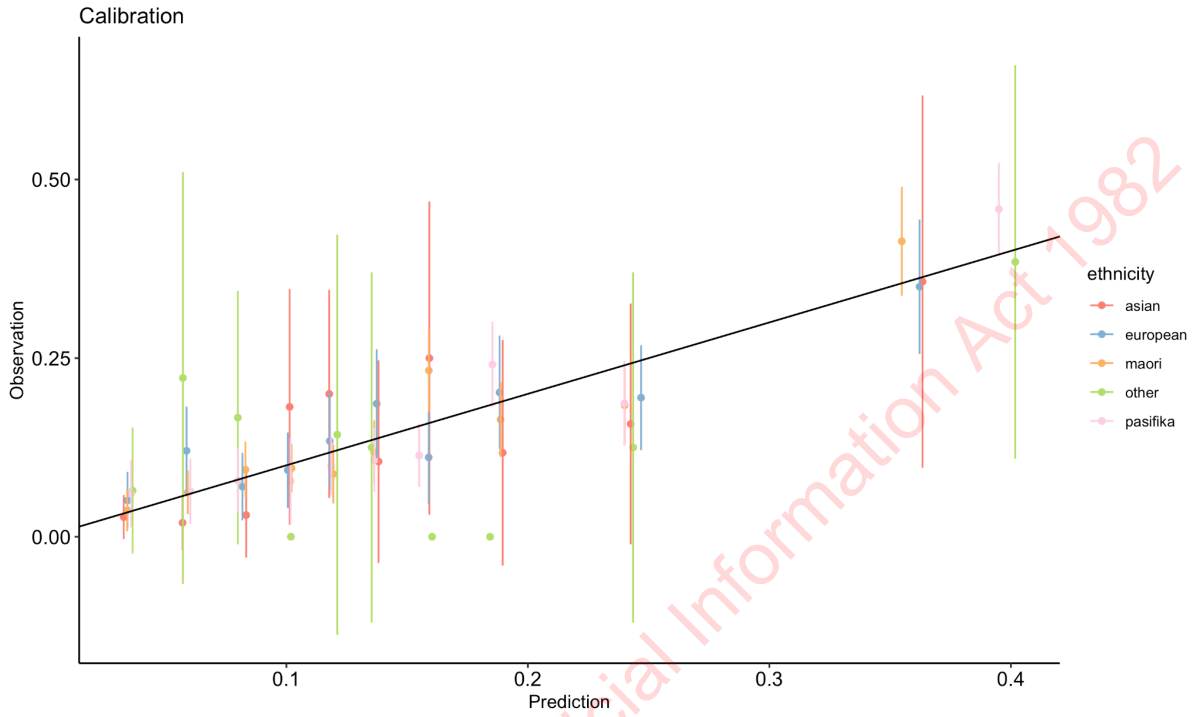
Hospital/Death		Actual	
		TRUE	FALSE
Predicted	TRUE	23	58
	FALSE	36	341

PRECISION DRIVEN HEALTH

Rates of hospitalisation and death by decile of estimated probability

Decile	Cases	Hospitalised	Death
10 (Estimated highest risk)	521	217 41.7%	14 2.7%
9	525	97 18.5%	0 0%
8	530	105 19.8%	3 0.6%
7	515	82 15.9%	0 0%
6	502	65 12.9%	1 0.2%
5	516	55 10.7%	0 0%
4	518	49 9.5%	1 0.2%
3	532	43 8.1%	0 0%
2	509	38 7.5%	0 0%
1 (Estimated lowest risk)	514	23 4.5%	0 0%

Calibration



Overfitting/generalisation (ability to predict well on unseen data)

+ The model, as built on delta data, will not generalise well for Omicron data assuming differences in risk of deterioration across the two variants.
+ Linear models with few parameters are less likely to overfit, however the "ethnicities" *asian* and *other* had low representation in the target variable (31 and 15 hospitalisations/deaths respectively) and the model will not generalise well for those groups.

Document 4

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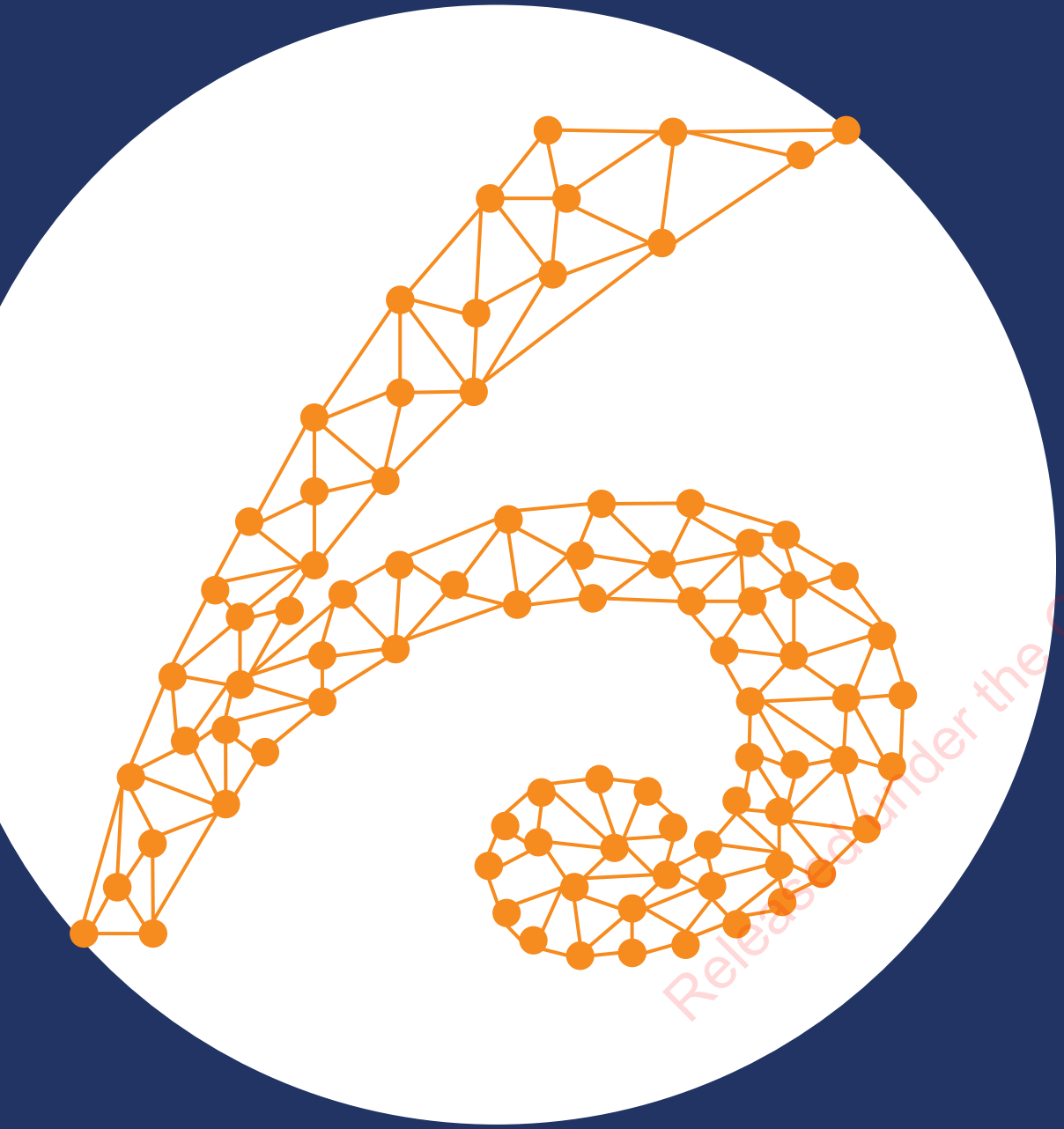


COVID Algorithm Development

Jon Herries

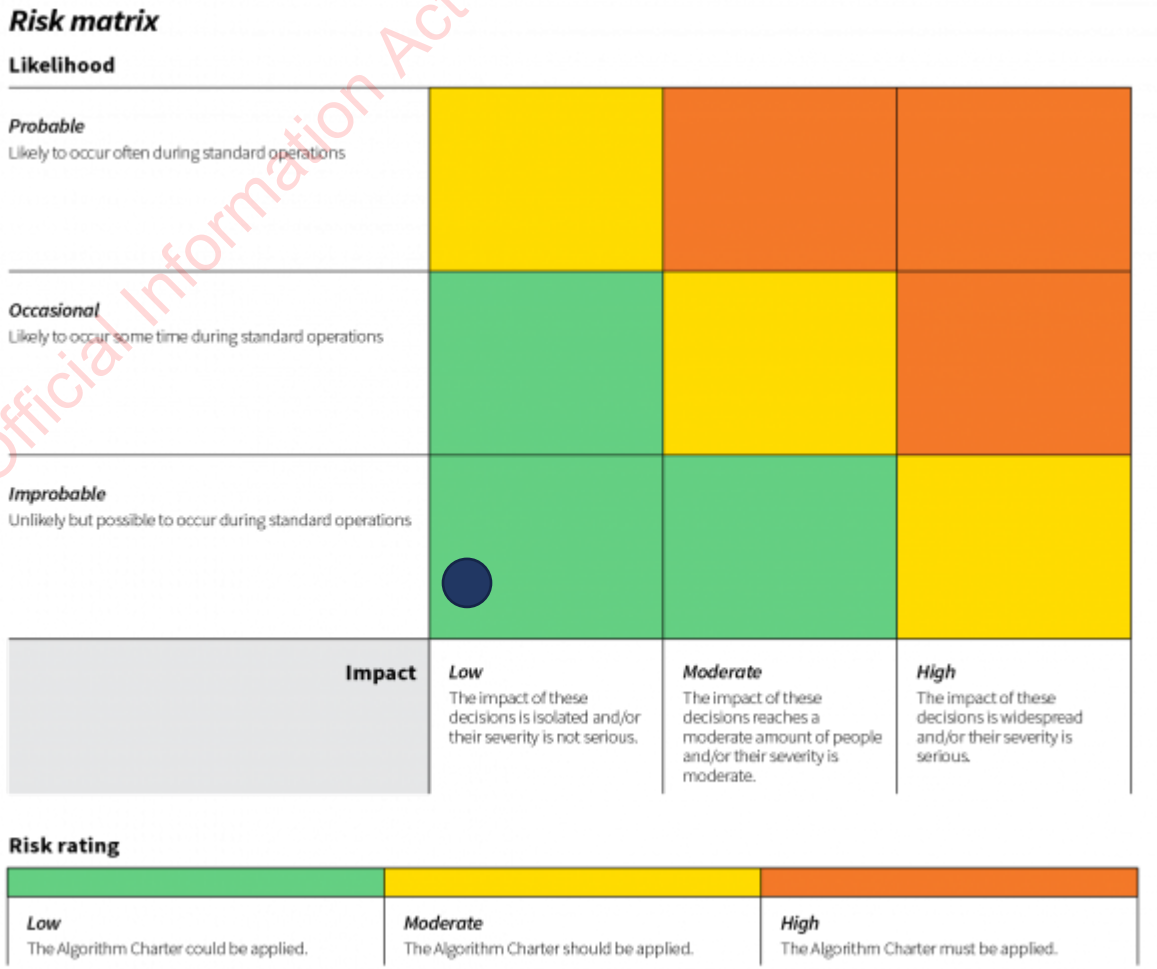
7 March 2022

Should we complete the Algorithm Charter

The algorithm charter is recommended to be used when there is likely to be a high likelihood many people will suffer an unintended adverse impact. In the context of developing this, it has to be considered that without a prioritisation model, many people will miss out on care who would benefit.

It has been scored in a low probability/low impact space due to:

- Acts as an input to a clinical assessment only
- Is used as part of a clinical assessment
- Training has been provided for this to users to help them understand how it has been created and the use case for it.
- It is a calculated score similar to use cases that are prevalent in healthcare already in many different clinical settings.



Controls associated with the commitments

Commitments	Ways to demonstrate the commitments	How are we addressing these?
Transparency - maintain transparency by clearly explaining how decisions are informed by algorithms.	Plain English documentation of the algorithm	Privacy Impact Assessment
	Making information about the data and processes available (unless a lawful restriction prevents this)	Privacy Impact Assessment
	Publishing information about how data are collected, secured and stored.	Privacy Impact Assessment
Partnership - Deliver clear public benefit through Treaty commitments by:	embedding a Te Ao Māori perspective in the development and use of algorithms consistent with the principles of the Treaty of Waitangi.	Governance Group
People - Focus on people by:	identifying and actively engaging with people, communities and groups who have an interest in algorithms, and consulting with those impacted by their use.	Publishing to Algorithm Hub
Data - Make sure data is fit for purpose by:	understanding its limitations	Technical Review
	identifying and managing bias.	Technical Review
Privacy, ethics, and human rights - Ensure that privacy, ethics and human rights are safeguarded by:	regularly peer reviewing algorithms to assess for unintended consequences and act on this information.	Governance Group
Human oversight - Retain human oversight by:	nominating a point of contact for public inquiries about algorithms	Governance Group/Publishing to Algorithm Hub
	providing a channel for challenging or appealing of decisions informed by algorithms	Governance Group
	clearly explaining the role of humans in decisions informed by algorithms.	Governance Group

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Evaluating the Risk Score for Call Prioritisation (National V1)

COVID–19 risk of hospitalisation model v1

Document version 1.0

Wednesday 4 May, 2022

Notes

- This document contains early results and is only intended for initial review of the evaluation process.
- All results are based on assumptions made with respect to data definitions.
- All hospitalisations are included with no specialty exclusions.
- Data for deaths in the community was neither identified nor available for this evaluation.
- Fully vaccinated is defined as "had two doses of vaccine". We note that there is at least one single dose vaccine (Janssen). Single dose vaccines have not been accounted for (therefore one dose = not fully vaccinated). We will require a more complete definition of "fully vaccinated" to account for these cases.[1]

Evaluation summary

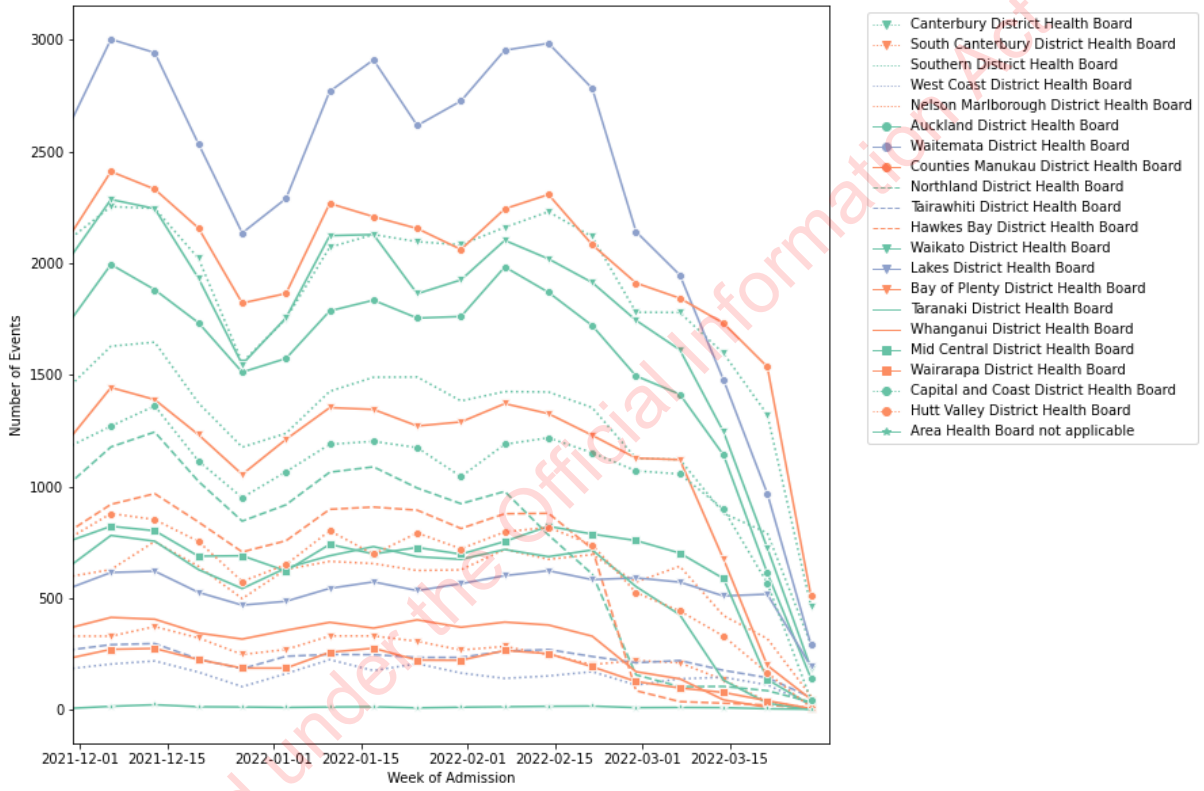
The evaluated model was originally developed using Delta data, and validating against this cohort is a useful review of the model's performance against the outcomes it was trained over.
The model is being applied to Omicron cases through the Simplified Risk Score for Call Prioritisation. Evaluating the model for the Omicron cohort tells us about the model performance in the context where it is being used.

This evaluation is part of a roadmap of development and improvement, each time we develop a model, that model is evaluated and that evaluation informs the next iteration.

[1] The names of vaccines found in the CPIR data set (first dose) are included in the Appendix

Data quality

The cohort for the Omicron analysis is defined as those with a positive covid diagnosis between 23 January to 14 February 2022 inclusive. The plot below shows count of unique hospital events by week/DHB in the hospitalisations data. The number of unique hospital events found drops off considerably after February 21. Given lag to hospitalisation, we assume some hospitalisations are missing in the data for this cohort.



The Omicron cohort (23 January - 14 February 2022)

Calling by risk score vs calling by random order

When used for call prioritisation for cases where little information is known about the patient, the model does a better job at capturing higher risk cases than calling patients in the order in which they are presented (which would be random).

For instance, we can look at the scenario where the tool is used to call the 10% of cases which have the highest scores, and compare rates of hospitalisation for this group against a randomly ordered list. Overall and across all groups, with varying

performance, the model identifies more people who require hospitalisation than the baseline prevalence (i.e. the number identified had those people been called at random).

Group	Total number of COVID positive cases (total number of hospitalised cases)	Calling by risk score ranking		Calling at random	
		Number in top 10% by risk score	% of the top risk group hospitalised (Number of hospitalised cases)	Number in randomly selected same number of COVID positive cases (% of the group in overall cases)	Group specific prevalence (Number of hospitalised cases)
Overall	3,151 (109)	316	12.3% (39)	316	3.5% (6)
Māori	324 (19)	35	11.4% (4)	32 (10.3%)	5.9% (2)
Over 60s	272 (29)	198	14.1%(28)	27 (8.6%)	10.7% (3)
Unvaccinated	133 (19)	98	16.3% (16)	13 (4.2%)	14.3% (2)

Highlights

- The model helps us identify higher risk people who are more likely to be hospitalised in the Omicron cohort.
- Overall, the model assigns higher risk to Māori and Pasifika than to other ethnicities. However, there are higher rates of hospitalisation across all risk levels for Māori and Pasifika cases compared to other ethnicities. There are two possible explanations for this. One is that the increase in risk for Māori and Pasifika may not be sufficiently large. Another consideration is that Māori and Pasifika experience higher hospitalisation rates overall regardless of COVID-19 status. It is possible that higher hospitalisation rates reflect this, noting that there is no distinction in the outcome between hospitalisation with and of COVID-19, and no exclusion of specialties that are unlikely to be COVID-19 related (e.g. gynaecology).
- Model performance for the unvaccinated (AUC-ROC 0.698) was just below the commonly used threshold for average performance (AUC-ROC 0.7).
- Model performance for the age group 60 and over was very good.

Evaluation measures

The simplified risk model is evaluated with:

- Rates of hospitalisation across predicted risk levels,
- AUC-ROC
- Classification metrics (e.g. accuracy, sensitivity, specificity).

All results are at the end of the document. The summary below focuses on rates of hospitalisation by risk level and AUC-ROC which both measure how well the simplified risk model ranks cases according to risk of hospitalisation (noting that the model is used for call ranking).[2]

Interpreting rates of hospitalisation across predicted risk levels

If the hospitalisation rate at higher risk levels is greater than the prevalence of hospitalisation overall, then we are more likely to call the 'right' people using the ranking, compared to random calling.

Interpreting AUC-ROC

AUC-ROC is a measure that indicates how good the model is at ranking people based on risk (how likely any two cases are correctly ordered). 0.5 indicates that the model is no better than random at ranking the cases in order of risk and 1 indicates a perfect model.[3] For the purposes of this document, AUC-ROC is defined as follows: 0.5-0.54 no better than random; 0.55 - 0.59 a little better than random; 0.6-0.64 better than random; 0.65-0.69 below average; 0.7-0.74 average; 0.75-0.79 good; 0.8+ very good.

Note that "average" refers to the commonly used threshold for average performance (AUC-ROC 0.7) and that "below average" does not necessarily imply substandard performance in the context.

[2] The classification metrics measure the model according to how it would perform as a classifier as opposed to a ranking tool (hospitalised vs not hospitalised, given a risk threshold which for this evaluation was set to 0.15).
[3] The statistical literature generally describes an AUC-ROC between 0.6 and 0.7 as 'poor' or 'average' and 0.7 - 0.8 as acceptable (for example, Hosmer & Lemeshow (2013). Applied logistic regression. p.177).

Variable definitions

Variables for the model are outlined in the table below. Included in the evaluation are people who have tested positive for COVID-19 between 30 November 2021 and 14 February 2022. Excluded from the evaluation are those who have COVID-19 status "Under investigation".

Variable	Definition
Tested positive for COVID-19	Between 30 November 2021 and 14 February 2022.
Outcome (Flag if hospitalised or death)	• Include a case in the outcome if hospitalised up to 28 days after and 2 days before a positive test for COVID-19. No specialty exclusions. • Deaths in the community are not included in the outcome due to data availability at the time of this evaluation. • There is no distinction between hospitalisation with and of COVID-19.
Age	Age in years. Exclude under 18.
Ethnicity	Level 1 ethnic codes for prioritised ethnicity: • "Māori" (2) • "Pacific Peoples" (3) • "Other" (1,4-9)
Vaccination status	Prior to testing positive: • Not vaccinated - No dose dates present • One dose - One dose date present, no two or three dose dates present • Fully vaccinated - Two or three dose dates present.

Overall results

- We note that AUC-ROC indicates how well the model ranks cases across all risk levels (in other words AUC-ROC measures how well the model ranks everyone across both high risk and low risk cases). In practice, the model is used for call prioritisation of the high risk cases. Therefore, while some of the AUC-ROC measures are low, if we look at just the hospitalisation rates at the higher risk level, we can see that across all groups the model performs better than random selection.
- As expected, hospitalisation rates increase as risk level increases for both the prospective Delta (30.11.21 - 22.01.22) and Omicron cohorts. This means that when the risk score is used for call prioritisation, the probability of calling the people who would be hospitalised is better than random selection.
- Rates of hospitalisation are affected by the measurement of the denominator (total covid cases), especially for the Omicron cohort. It is expected that actual rates of hospitalisation would be lower across all groups than measured here due to undetected cases.
- The hospitalisation rate for the Omicron cohort is lower than for the Delta cohort (3.5% cf 8.3%).
- The model had average overall performance in prospective evaluation for both cohorts combined (30.11.21-14.02.22) (0.715 AUC-ROC).
- The model had higher performance for the Delta cohort compared to the data the model was built on in January 2022, based on Delta data up until 29.11.22 (0.717 cf 0.7 AUC-ROC).
- Performance for the Omicron cohort is below average (0.683 AUC-ROC) and lower than that for the Delta cohort. This was expected as the model was trained on Delta cases.

Performance for groups

- Hospitalisation rates increased with risk level across all sub-groups (age, ethnicity, vaccination status).
- Hospitalisation rates were higher for people who were not fully vaccinated, and for Māori and Pasifika.

Age

- When broken down by risk level, the age trend is less consistent, likely related to group composition and measurement error in the denominator.

- For the Delta cohort, model performance was good for the 40-59 year age group (AUC-ROC 0.781), and below average for 18-39 years (AUC-ROC 0.667) and for over 60s (AUC-ROC 0.691).
- For the Omicron cohort, model performance was no better than random for the 40-59 year age group (AUC-ROC 0.540), better than random for the 18-39 year age group (0.648), and very good for over 60s (AUC-ROC 0.829). We note that the performance of the middle age bracket may be influenced by people in this cohort being hospitalised for reasons other than COVID-19 (there is no distinction between hospitalisation with and of COVID-19 in the outcome, nor is there exclusion of certain specialties).

Ethnicity

- There are higher rates of hospitalisation for low risk Māori and Pasifika cases compared to other ethnicities. There are two possible explanations for this. One is that the increase in risk for Māori and Pasifika may not be sufficiently large. Another consideration is that Māori and Pasifika experience higher hospitalisation rates overall regardless of COVID-19 status. It is possible that higher hospitalisation rates at lower risk levels reflect this, noting that there is no distinction in the outcome between hospitalisation with and of COVID-19, and no exclusion of specialties that are unlikely to be COVID-19 related (e.g. gynaecology).
- For the Delta cohort, performance was good for Pasifika (AUC-ROC 0.799), average for Māori (AUC-ROC 0.719) and below average for other ethnic groups (AUC-ROC 0.673)
- For the Omicron cohort, performance was better than random for Māori (AUC-ROC 0.609) and below average for Pasifika (AUC-ROC 0.672), and other ethnic groups (AUC-ROC 0.688)

Vaccination status

- For the Delta cohort, performance was a little better than random for the fully vaccinated (AUC-ROC 0.598), below average for not fully unvaccinated[4] (AUC-ROC 0.689) and average for the unvaccinated (AUC-ROC 0.710)
- For the Omicron cohort, performance was better than random for the fully vaccinated (AUC-ROC 0.638) and below average for not fully vaccinated (AUC-ROC 0.677) and unvaccinated (AUC-ROC 0.698).

[4] 'Not fully vaccinated' combines those who are unvaccinated and those who have had one dose.

Background

The COVID–19 risk of hospitalisation model v1, also known as the "simplified risk model" is available to support local Hubs with call prioritisation. This model predicts risk of hospitalisation for people who have tested positive for COVID-19. The model was trained on Northern Region COVID-19 data from the start of the Delta outbreak until late November 2021 (people who tested positive for COVID-19 19/08/2021 - 29/11/2021). The model was developed to be used as a risk stratification tool to determine contact priority at times where a covid positive person has not used the self service portal and there is little clinical information otherwise available for that person.

The simplified risk model has three predictor variables - Age, Ethnicity, and Vaccination Status. These variables were chosen for their relevance to clinical deterioration and their ready availability at the national level. The intention has been to build on this model over time by incorporating comorbidity variables. Due to time and data constraints, this model was not prospectively evaluated before being rolled out.

The Ministry of Health would like to now prospectively evaluate this model to assess its performance. Hospitalisation, Age, Ethnicity and vaccination status data will be used to score people who tested positive for COVID-19 from 30 November 2021 up to 14 February 2022[5].

Evaluation Approach

- Evaluation cohorts
    - Cohort 1 - People aged over 18 who tested positive for COVID-19 between November 30 2021 and January 22, 2022 (Delta Cases)
    - Cohort 2 - People aged over 18 who tested positive for COVID-19 between January 23, 2022 (Omicron and Delta) and 14 February, 2022
    - Cohorts will be further stratified by age, ethnicity and vaccination status.
    - The Risk Score was available from 11 March 2022
- Outcome measures

[5] We understand NMDS hospitalisation data is currently available up until the end of February 2022. This data covers discharges only. The cohort of people who tested positive for COVID-19 after 14 February has had insufficient time to have been both hospitalised and discharged by 28 February and is therefore excluded.

    - Primary outcome measure - hospitalisation defined as hospitalisation up to 28 days after a positive test result and 48 hours before a positive test result.
    - Secondary outcome measures - None proposed
- Evaluation questions
    - What is the observed rate of hospitalisation within groups identified by the Risk Score as being at low (risk score <0.1), medium (risk score >=0.1 and risk score <0.2) or high risk (risk score >=0.2) of hospitalisation?
    - How does this vary by age, ethnicity and vaccination status? (depending on sample sizes available in the data)
    - How does this vary between the Delta and Omicron variants?
    - How does this vary over time (alongside total reported cases)?
    - How does this vary by DHB region? (if applicable) This can be reviewed alongside qualitative feedback on where and how the Risk Score is being used.
- Evaluation metrics
    - Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and F1 Score (a balanced measure of precision and recall).
- Limitations
    - Outcomes are likely to be affected by the total volume of COVID-19 cases and strain on the system at a point in time. This has varied during the course of the Omicron outbreak and is not accounted for in this approach although we propose to review the risk score over time.
    - A range of local and national risk scores are being used by local Hubs. The use of these scores for prioritisation is expected to have some positive impact on people's outcomes. This means it is difficult to separate how good the score is at predicting risk vs. the impact of using the score for prioritisation of clinical assessment and intervention which lowers risk of hospitalisation.
    - Some regions, such as the Northern Region, are using locally developed risk scores that take more information about a person's health into account and use of the score for prioritisation may be expected to have a larger positive impact.
    - We expect that a large number of true positive COVID cases will be missing where people have not tested or not reported RAT results.

Where these people were hospitalised, we understand that a positive test result would be backfilled in their record. We are therefore likely to be missing a large cohort of people who tested positive and were not hospitalised. This potentially skews the evaluation cohort towards higher risk people.

- Testing and hospitalisation reflect access to healthcare and don't provide a complete picture of need for healthcare. This evaluation approach may miss individuals who needed/continue to need greater care.
- The window for hospitalisation has been defined as 28 days after a positive test. We note that we plan to include people who tested positive up to two weeks before the expected maximum date of the NMDS data. We may not have the full hospitalisation window for some patients who tested positive between 31 January 2022 and 14 February 2022 (due to data processing lags).
- NMDS hospitalisation data relates to discharges. Any person who is included in our evaluation data who was discharged after 28 February may not be flagged as hospitalised as their hospitalisation may not be visible (due to data processing lags).
- Deaths in the community will not be included due to data availability at the time of the evaluation.
- There are no specialty exclusions for who is hospitalised. Nor is there a distinction between being hospitalised with or of COVID-19. This may mean hospitalisation rates in lower risk categories are higher than expected for groups that have usually higher overall hospitalisation rates than the prevalence.

Breakdown of the Omicron mixed cohort

By age

Hospitalisation (Number of cases)	Age	Percentage in the hospitalisation group
Not hospitalised (3,042)	18-39yr	63.9%
	40-59yr	28.1%
	60yr+	8.0%
Hospitalised (109)	18-39yr	48.6%
	40-59yr	24.8%
	60yr+	26.6%

By ethnicity

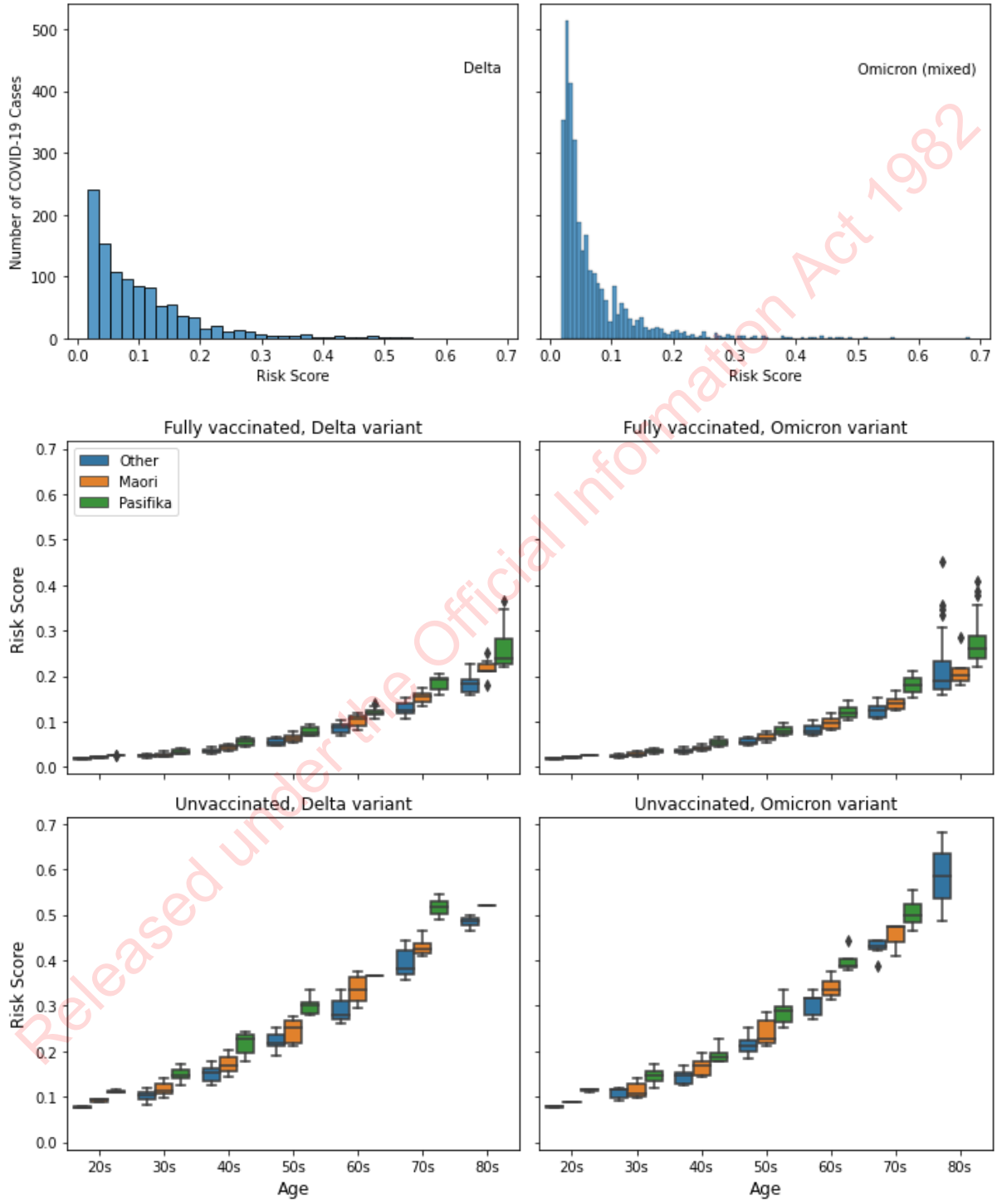
Hospitalisation (Number of cases)	Ethnicity	Percentage in the hospitalisation group
Not hospitalised (3,042)	Māori	10.0%
	Pasifika	38.6%
	Other	51.3%
Hospitalised (109)	Māori	17.4%
	Pasifika	49.5%
	Other	33.0%

By vaccination status

Hospitalisation (Number of cases)	Vaccination Status	Percentage in the hospitalisation group
Not hospitalised (3,042)	Fully vaccinated	95.2%
	One dose	1.1%
	Unvaccinated	3.7%
Hospitalised (109)	Fully vaccinated	79.8%
	One dose	2.8%
	Unvaccinated	17.4%

Detailed Early Evaluation Results

Risk score distribution



Hospitalisation rates

Risk levels are defined as:

Risk score	Risk level
<0.1	LOW
>= 0.1 and < 0.2	MEDIUM
>= 0.2	HIGH

Overall rates

Risk Level	% Hospitalised (Sample size)	
	Delta	Omicron (mixed)
OVERALL	8.3% (1,056)	3.5% (3,151)
LOW	4.0% (645)	2.3% (2,571)
MEDIUM	10.7% (298)	4.7% (448)
HIGH	26.6% (113)	21.2% (132)

Interpretation

- Used as a ranking tool, the risk score means we would be more likely to call people who would be later hospitalised than if we called people at random.
- For the Omicron cases, had we called the 132 cases in the highest risk group, we would have reached ~28 people (21.2%) who were eventually hospitalised.
- By contrast, had we called 132 people at random, we would have reached ~5 people (based on prevalence of 3.5%) who were eventually hospitalised. This is 18% of the number successfully identified above using the risk score.

By age

Note that at some risk levels across both cohorts, the hospitalisation rate for the 18-39 year age group is higher than for older age groups. This may be due to missing cases from the denominator where people with COVID-19 have either not been tested, or not reported a test. Small sample size is also a factor. Group composition within each age band, with respect to vaccination status and ethnicity, may also be a contributing factor.

Cohort	Risk Level	% Hospitalised (Sample size)		
		18 - 39yr	**40 - 59yr**	**60yr+**
Delta	**OVERALL**	7.1% (619)	7.7% (324)	16.8% (113)
	LOW	4.8% (441)	2.5% (204)	NA[6]
	MEDIUM	12.4% (169)	7.4% (54)	9.3% (75)
	HIGH	22.2% (9)	24.2% (66)	31.6% (38)
Omicron (mixed)	**OVERALL**	2.6% (1,997)	3.1% (882)	10.7% (272)
	LOW	2.3% (1,926)	2.5% (645)	NA
	MEDIUM	11.6% (69)	3.0% (199)	3.9% (180)
	HIGH	50.0% (2)	13.2% (38)	23.9% (92)

[6] In the model calculation, this age group cannot be assigned a low risk score.

By ethnicity

Cohort	Risk Level	% Hospitalised (Sample size)		
		Pasifika	Maori	Other
Delta	OVERALL	10.8% (157)	10.2% (335)	6.6% (564)
	LOW	2.4% (85)	5.1% (137)	4.0% (423)
	MEDIUM	12.8% (47)	9.0% (144)	12.2% (107)
	HIGH	36.0% (25)	25.9% (54)	20.6% (34)
Omicron (mixed)	OVERALL	4.4% (1,229)	5.9% (324)	2.2% (1,598)
	LOW	3.1% (911)	4.6% (262)	1.4% (1,398)
	MEDIUM	4.5% (245)	8.3% (48)	3.9% (155)
	HIGH	20.6% (73)	21.4% (14)	22.2% (45)

By vaccination status

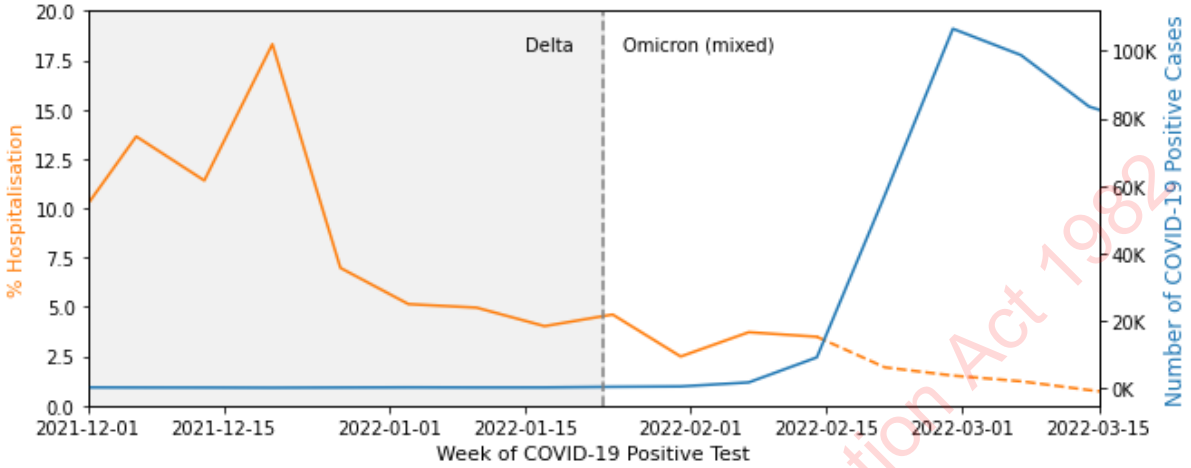
Cohort	Risk Level	% Hospitalised (Sample size)	
		Fully vaccinated	Not fully vaccinated
Delta	OVERALL	4.9% (673)	14.4% (383)
	LOW	3.6% (553)	6.5% (92)
	MEDIUM	7.8% (102)	12.2% (196)
	HIGH	27.8% (18)	26.3% (95)
Omicron (mixed)	OVERALL	2.9% (2,983)	13.1% (168)
	LOW	2.3% (2,536)	5.7% (35)
	MEDIUM	3.5% (372)	10.5% (76)
	HIGH	21.3% (75)	21.1% (57)

By DHB

Because the sample of data available is limited to the first two weeks of the Omicron outbreak, the majority of cases were still in the Auckland region. A by DHB analysis would not be meaningful in the context of this data.

Over time

Overall



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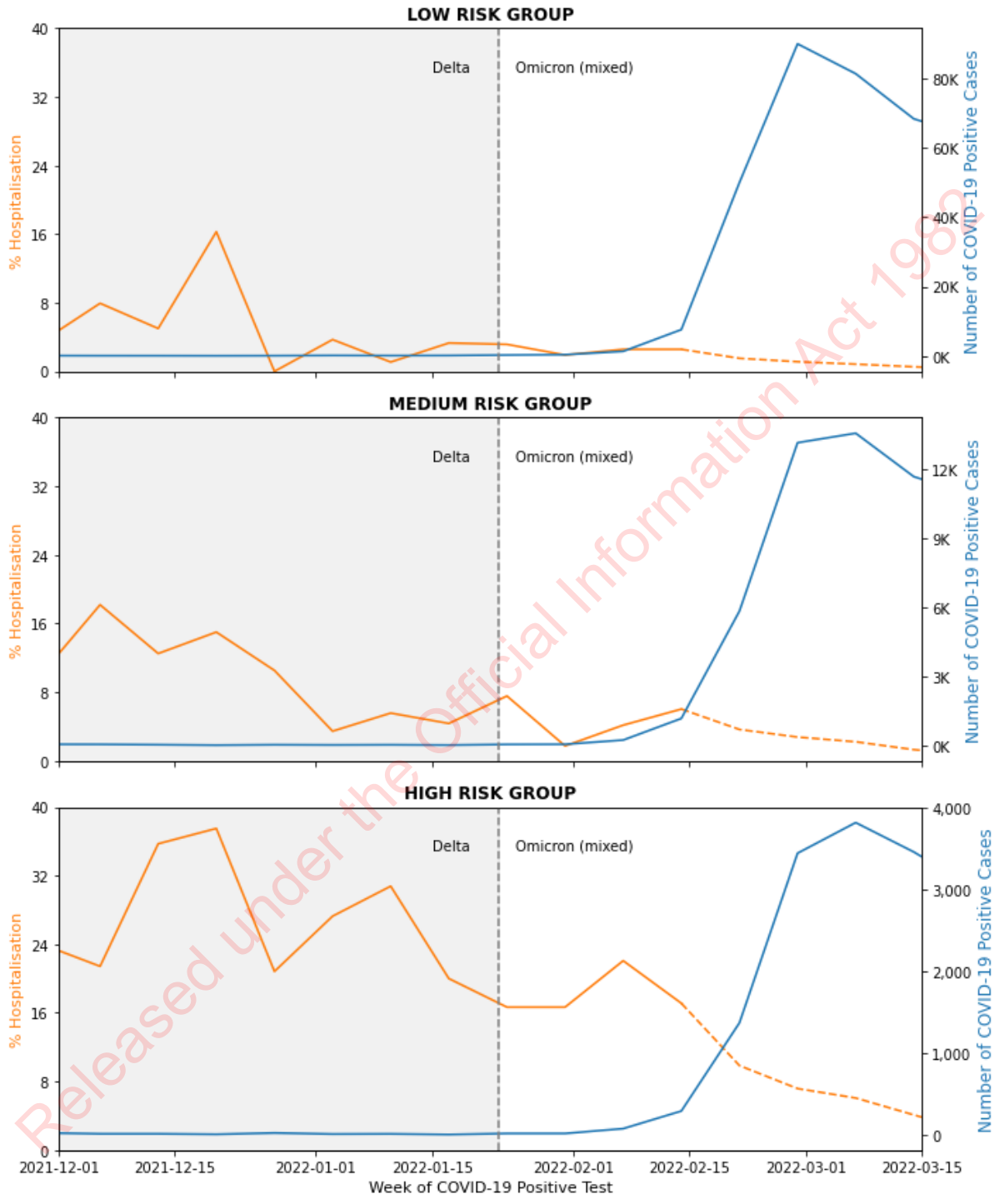
By risk groups



Metrics

Classification metrics (Accuracy, Sensitivity, Specificity, Precision, Negative Predictive Value, F1 Score and Balanced Accuracy) are based on a risk score threshold of 0.15, above which a person is predicted to be hospitalised. The choice of risk score threshold will affect the classification metrics. As the threshold changes, some metrics will improve, others will worsen. The choice of threshold therefore depends on the use case. For the call prioritisation use case, we wish to minimise the number of cases where someone is classified as not hospitalised when they were, in fact, hospitalised (false negative). Therefore, we have tuned this threshold to maximise Negative Predictive Value.

An explanation of the classification metrics is included in the Appendix. An explanation of AUC-ROC is in the Evaluation Measures section.

Overall

	Overall	Delta	Omicron (mixed)
Sample Size	4,207	1,056	3,151
Prevalence	4.68%	8.33%	3.46%
AUC-ROC	0.715	0.717	0.683
Accuracy	0.879	0.794	0.908
Sensitivity (Recall)	0.411	0.511	0.330
Specificity	0.902	0.819	0.929
Precision	0.171	0.205	0.142
Neg Pred Value	0.969	0.949	0.975
F1 score	0.242	0.292	0.199
Balanced Accuracy	0.657	0.665	0.629

By age

	Overall	Delta			Omicron (mixed)		
		18-39yr	40-59yr	60yr+	18-39yr	40-59yr	60yr+
Sample Size	4,207	619	324	113	1,997	882	272
Prevalence	4.68%	7.11%	7.72%	16.81%	2.65%	3.06%	10.66%
AUC-ROC	0.715	0.667	0.781	0.691	0.648	0.54	0.829
Accuracy	0.879	0.859	0.778	0.478	0.962	0.931	0.438
Sensitivity (Recall)	0.411	0.295	0.720	0.737	0.057	0.185	0.966
Specificity	0.902	0.903	0.783	0.426	0.987	0.954	0.374
Precision	0.171	0.188	0.217	0.206	0.103	0.114	0.156
Neg Pred Value	0.969	0.944	0.971	0.889	0.975	0.974	0.989
F1 score	0.242	0.230	0.333	0.322	0.073	0.141	0.268
Balanced Accuracy	0.657	0.599	0.751	0.581	0.522	0.570	0.670

By ethnicity

	Overall	Delta			Omicron (mixed)		
		Other	Māori	Pasifika	Other	Māori	Pasifika
Sample Size	4,207	564	335	157	1,598	324	1,229
Prevalence	4.68%	6.56%	10.15%	10.83%	2.25%	5.86%	4.39%
AUC-ROC	0.715	0.673	0.719	0.799	0.688	0.609	0.672
Accuracy	0.879	0.851	0.710	0.764	0.942	0.877	0.872
Sensitivity (Recall)	0.411	0.297	0.676	0.647	0.417	0.158	0.333
Specificity	0.902	0.89	0.714	0.779	0.954	0.921	0.897
Precision	0.171	0.159	0.211	0.262	0.172	0.111	0.129
Neg Pred Value	0.969	0.947	0.951	0.948	0.986	0.946	0.967
F1 score	0.242	0.208	0.322	0.373	0.244	0.130	0.187
Balanced Accuracy	0.657	0.594	0.695	0.713	0.685	0.540	0.615

By vaccination status[7]

	Overall	Delta		Omicron (mixed)	
		Fully vaccinated	Not fully vaccinated	Fully vaccinated	Not fully vaccinated
Sample Size	4,207	673	383	2,983	168
Prevalence	4.68%	4.90%	14.36%	2.92%	13.10%
AUC-ROC	0.715	0.598	0.689	0.638	0.677
Accuracy	0.879	0.900	0.606	0.931	0.500
Sensitivity (Recall)	0.411	0.212	0.691	0.253	0.636
Specificity	0.902	0.936	0.591	0.951	0.479
Precision	0.171	0.146	0.221	0.135	0.156
Neg Pred Value	0.969	0.958	0.919	0.977	0.897
F1 score	0.242	0.173	0.335	0.176	0.250
Balanced Accuracy	0.657	0.574	0.641	0.602	0.558

	Overall	Delta		Omicron (mixed)	
		Fully vaccinated	Unvaccinated	Fully vaccinated	Unvaccinated
Sample Size	4,207	673	276	2,983	133
Prevalence	4.68%	4.90%	15.58%	2.92%	14.29%
AUC-ROC	0.715	0.598	0.71	0.638	0.698
Accuracy	0.879	0.900	0.547	0.931	0.414
Sensitivity (Recall)	0.411	0.212	0.814	0.253	0.737
Specificity	0.902	0.936	0.498	0.951	0.36
Precision	0.171	0.146	0.23	0.135	0.161
Neg Pred Value	0.969	0.958	0.935	0.977	0.891
F1 score	0.242	0.173	0.359	0.176	0.264

[7] The first table compares those who are fully vaccinated and those who are not fully vaccinated (unvaccinated and one dose). The second table compares those who are fully vaccinated and those who are unvaccinated.

Balanced Accuracy	0.657	0.574	0.656	0.602	0.548

References

Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression (Vol. 398). John Wiley & Sons.

Appendix

Risk Model Performance Metrics

These metrics are based on classifying people with estimated risk over the threshold as 'at risk' and those with estimated risk beneath the threshold as 'not at risk'. In practice, there are likely to be multiple risk groups used for specific use cases.

Sensitivity/Recall: What proportion of people with hospitalisation or mortality recorded are classified as at risk?

Specificity: What proportion of people without hospitalisation or mortality recorded are classified as not at risk?

PPV/Precision: Of the people classified as being at risk, what proportion did have hospitalisation or mortality recorded ?

NPV: Of the people classified as being not at risk, what proportion did not have hospitalisation or mortality recorded ?

F1 Score: Harmonic mean of precision and recall (balanced metric to describe precision and recall)

First dose vaccinations in CPIR

Vaccine name (as it appears in CPIR)	Count of first dose
Pfizer BioNTech COVID-19	4,043,725
Paediatric Pfizer	260,427
AstraZeneca	16,309
Moderna	3,555
Covishield	2,677
CoronaVac	2,221
Sinopharm	1,859
Novavax	1,635
Janssen	1,417
Sputnik V	533
Sinopharm Inactivated (Vero Cells)	230
Covaxin	160
ZIFIVAX / ZF2001 / RBD-Dimer	48
Covidecia / Ad5-nCOV	38
KCONVAC / SARS-CoV-2 Vaccine (Vero Cells)	25
EpiVacCorona	21
Sputnik Light	18
COVID-19 Inactivated Vaccine/COVIran Barekat	10
MVC-COV1901	4
COVAX-19/SpikoGen	2
Abdala / CIGB-66	2
Pfizer BioNTech 19	1
Pfizer	1
FAKHRAVAC(MIVAC)	1
TAK-919 (Moderna formulation)	1
KoviVac	1
Sinopharm Inactivated	1
Coronavac	1
EpiVacCorona - N	1

Document 6

COVID-19 Care in the Community

Risk Score for Call Prioritisation (Version 1)

COVID-19 Care in the Community
Ministry of Health

Te Kāwanatanga o Aotearoa
New Zealand Government

MINISTRY OF HEALTH
MANATŪ HAUORA

Unite against COVID-19

COVID-19 Care in the Community

Document 6

Risk Score for Call Prioritisation

The COVID-19 Care in the Community team and the Data and Digital Directorate have developed a population-based risk stratification tool (the **Risk Score for Call Prioritisation**, or, **Risk Score** for short) that will be part of the COVID-19 digital platform when a positive case is identified.

- When someone tests positive for COVID-19, they are sent a text notification. The text includes a link to an online assessment form, and more information about managing their symptoms.
- If the person does not complete the form in 24 hours, the Care Coordination Hubs (CCH) arrange a follow up call. If text is not possible (i.e. no mobile access or mobile number is not known, then the CCH refer to a community provider for a home visit.
- The risk score tool helps the Hub assess **who is likely to need a follow up call sooner**, if there is a high number of people isolating at home in the community**.**
- It uses population data, like age and ethnicity, to determine whether someone with COVID-19 is more likely to be able to safely manage their recovery at home, or whether they may require additional clinical support.
- Age and ethnicity data is collected through the National Health Index (NHI).

While the majority of people notified that they have COVID-19 will complete the online self-assessment tools which gathers information around co-morbidities and other health conditions, many people will not, leaving the Care Coordination Hubs unaware of the persons underlying conditions and current symptoms.

The **Risk Score** can be used here to sort and prioritise people for call back.

COVID-19 Care in the Community

Document 6

Risk Score for Call Prioritisation

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- In this first version, the Risk Score **should not be used for clinical decision-making.**
- **It is aimed at Hub Users,** helping the Hub assess **who is likely to need a follow up call sooner**, if there is a high number of people isolating at home in the community.

COVID-19 Care in the Community

Document 6

Risk Score for Call Prioritisation

The COVID-19 Care in the Community team and the Data and Digital Directorate have developed a population-based risk stratification tool (the **Risk Score for Call Prioritisation**, or, **Risk Score** for short) that will be part of the COVID-19 digital platform when a positive case is identified.

How is the risk score calculated?

- The risk score is calculated using a mathematical formula that takes age, ethnicity and vaccination status as inputs. Being older, unvaccinated or having had one vaccination dose, and having Māori or Pasifika ethnicity all increase someone's estimated risk
- As someone's age increases, so does their risk score, and the impact of age on their risk score – the mathematical formula means the score changes along with the information that it relies on. The formula means we need to consider the risk factors taken together.
    - For example, adding 5 years to someone's age at 70 has a bigger impact on total risk than adding 5 years at age 40.
    - This means that how much the other factors contribute to someone's total risk also changes with their age.
- Across all age groups:
    - the greatest increase in risk comes from being unvaccinated, then having a single vaccination dose
    - the ethnicity data factor reflects the need to achieve better health outcomes for Māori and Pasifika
- Please note that there are complex relationships between these risk factors (and health conditions not included in the model) across our population and weightings of risk factors should not be taken in isolation.
- The risk score is not used for clinical decision making. It helps the Hub to identify who is likely to need a follow up call sooner.
- The risk score supports identifying high risk people for call prioritisation but shouldn't be interpreted as a 'standalone' number outside of this use.

COVID-19 Care in the Community

Risk Score for Call Prioritisation

Example contributions of individual risk factors for different age groups

Age	Factor	Contribution to risk score
30	**Baseline***	**0.0268**
	Māori	+0.0049
	Pasifika	+0.0126
	Dose 1	+0.0332
	Unvaccinated	+0.0953
40	**Baseline***	**0.0428**
	Māori	+0.0076
	Pasifika	+0.0196
	Dose 1	+0.0510
	Unvaccinated	+0.1412
50	**Baseline***	**0.0675**
	Māori	+0.0117
	Pasifika	+0.0298
	Dose 1	+0.0761
	Unvaccinated	+0.2001
60	**Baseline***	**0.1050**
	Māori	+0.0173
	Pasifika	+0.0437
	Dose 1	+0.1087
	Unvaccinated	+0.2670
70	**Baseline***	**0.1598**
	Māori	+0.0245
	Pasifika	+0.0609
	Dose 1	+0.1460
	Unvaccinated	+0.3300

* Baseline risk is for a patient of the same age who is fully vaccinated and not Māori or Pasifika ethnicity. Please note that risk factors are independently additive to the baseline risk but not in combination – the risk model equation needs to be used for multiple factors (age, ethnicity and vaccination status).

MINISTRY OF HEALTH
MANATŪ HAUORA

Risk Score for Call Prioritisation training (NCTS)

Training Guide

COVID-19 Care in the Community

Risk Score for Call Prioritisation

The COVID-19 Care in the Community team and the Data and Digital Directorate have developed a population-based risk stratification tool (the **Risk Score for Call Prioritisation**, or, **Risk Score** for short) that will be part of the COVID-19 digital platform when a positive case is identified.

- The tool helps to **identify** who needs to be **prioritised for contact** for the first assessment which determines whether their COVID-19 care needs to be supported with active care management or the self-service pathway.
- The tool will **support** Care Coordination Hubs by **prioritising outreach** from the hub to those who have not responded to the initial text outreach to indicate that they are positive for COVID-19.
- In this first version, the Risk Score **should not be used for clinical decision-making**. As we develop future versions the model, we will continue to undertake additional peer reviews to validate the model.
- The tool is a simplified model using **age, ethnicity and vaccination status data** to **inform risk of hospitalisation** due to COVID-19. This uses 0, 1 or 2 doses. Booster information will be included in future versions of the model. This model has been developed and evaluated using local data.

While the majority of people notified that they have COVID-19 will complete the online self-assessment tools which gathers information around co-morbidities and other health conditions, many people will not, leaving the Care Coordination Hubs unaware of the persons underlying conditions and current symptoms.

The **Risk Score** can be used here to sort and prioritise people for call back.

COVID-19 Care in the Community

Risk Score for Call Prioritisation

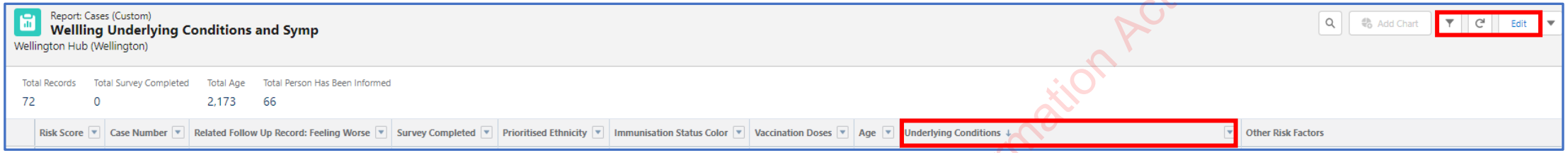
Example contributions of individual risk factors for different age groups

Age	Factor	Contribution to risk score
30	**Baseline***	**0.0268**
	Māori	+0.0049
	Pasifika	+0.0126
	Dose 1	+0.0332
	Unvaccinated	+0.0953
40	**Baseline***	**0.0428**
	Māori	+0.0076
	Pasifika	+0.0196
	Dose 1	+0.0510
	Unvaccinated	+0.1412
50	**Baseline***	**0.0675**
	Māori	+0.0117
	Pasifika	+0.0298
	Dose 1	+0.0761
	Unvaccinated	+0.2001
60	**Baseline***	**0.1050**
	Māori	+0.0173
	Pasifika	+0.0437
	Dose 1	+0.1087
	Unvaccinated	+0.2670
70	**Baseline***	**0.1598**
	Māori	+0.0245
	Pasifika	+0.0609
	Dose 1	+0.1460
	Unvaccinated	+0.3300

* Baseline risk is for a patient of the same age who is fully vaccinated and not Māori or Pasifika ethnicity. Please note that risk factors are independently additive to the baseline risk but not in combination – the risk model equation needs to be used for multiple factors (age, ethnicity and vaccination status).

Risk Score for Call Prioritisation | Cases that have not had clinical assessment in 24 hours

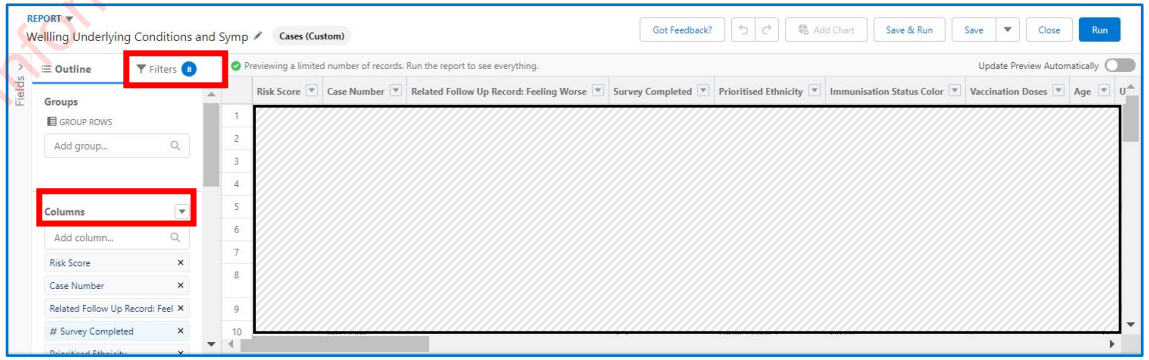
The risk score is a field in the back end of the NCTS that assigns a numeric score (0-1) to each case. A number closer to 1 is considered higher risk; a number closer to 0 is considered lower risk. This number can be used to prioritise patient call-backs if the Care Coordination Hubs has not had contact within 24 hours of their positive COVID-19 test result.



Please note that your page view may look slightly different from that shown here.

Tip:
You could build multiple reports to help display the data in multiple ways continuously, you can display these reports in a dashboard to help to actively manage the data and the days workload continuously

If you want help to create, edit and manage a report, we can offer different options of training, advice and guidance around this, please reach out to the Care in the Community team

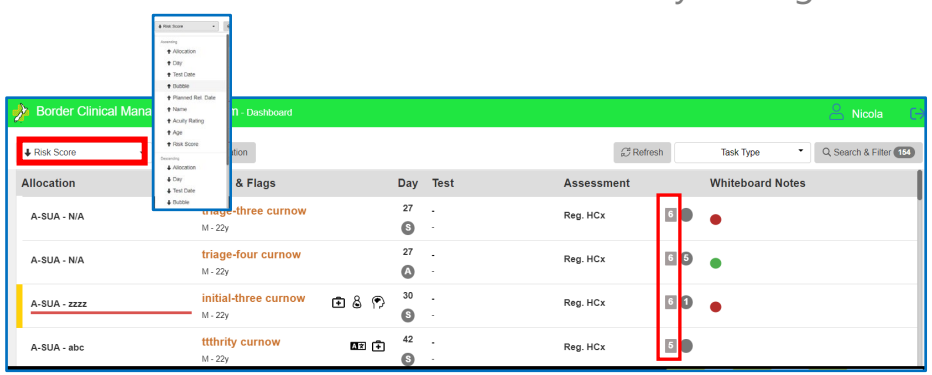


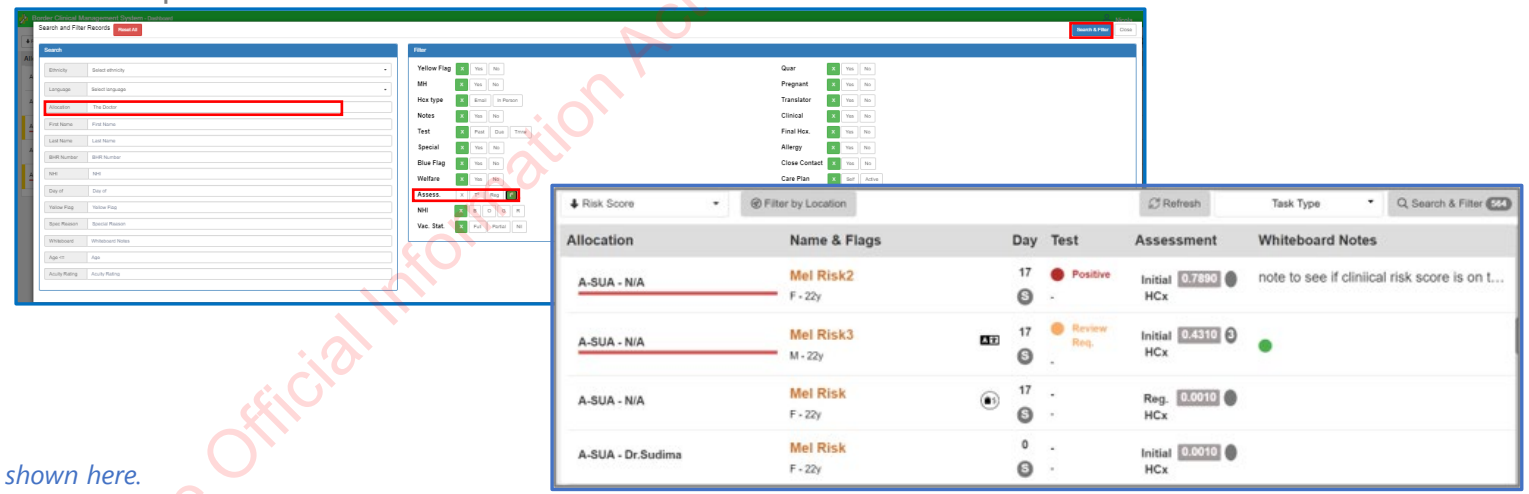
- The Risk Stratification tool uses information from the NHI data base to assign a number to each Case record in the NCTS, this number is found on a field called the Risk Score
- The Risk Score factors the details of **Age**, **Prioritised Ethnicity** and **Vaccination** status
- This number represents Public Risk rather than Clinical Risk and is not considered a clinical assessment
- The Risk Score is attached to the back end of a Case record, but can be viewed via a report,
- Reports can be filtered, ordered and sorted to help you view and rearrange sets of data.
- You can view multiple case's data in a single report to help to see the different circumstances or scenarios that people might be facing to help to decide which patients are higher or lower risk when it comes to COVID 19

- This report shows us open Cases under the management of a specific Hub, that have not completed their self survey form or been called by a contact tracer or a someone from a clinical perspective to date
- You can use the Filter and Edit buttons at any time in the report to make the report work to your advantage, you can add, remove or reorder the columns, you can alter the filters with the tab in the upper left, then click Run, to recalculate and show the new data set
- Reports can be found by using the Dropdown menu in the task bar. Navigate to the reports folders to find the one you want to use

Risk Score for Call Prioritisation| Using the risk score to prioritise call backs in CCCM

The risk score is a number (0-1) pulled through from the NCTS and assigns a number to each person. A number closer to 1 is considered higher risk; a number closer to 0 is considered lower risk. The risk score can be used to prioritise patient call-backs if the Care Coordination Hubs has not had contact within 24 hours of their positive COVID-19 test result. The Dashboard can be sorted by descending risk number, then Search & Filter the data to show your organisation and to prioritise Initial Health Checks.





Please note that your page view may look slightly different from that shown here.

- You can rearrange the data in the dashboard to display highest to lowest risk number, use the Sort By Menu to select the descending Risk Score option, to but the highest numbers at the top of the page.
- The day column will tell you if these people are under self or active management – note: all new records will default to self management and you can change the management plan on an individual basis.

- The Search and Filter button is a menu you can use to generate an order of workload, for example you can make the dashboard display only your organisations patients that need a call back or to be reviewed today.
- This menu has two parts to it, the left side, Search – will display only the records with that criteria. The right side, Filter - will hide the records that don't display that specific criteria.
- For example; you can sort the dashboard by the highest risk score and to only show records that have been allocated to your organisation that have not completed an initial health check.

- Enter your organisations name into the Allocation field on the left side of the menu, this will list only those that have been assigned to your organisation.
- You can also turn on the option to only see the initial assessment – this is a good indication of those who have not yet been contacted in regards to clinical assessment.
- To save these changes use the blue Search & Filter button at the top right of the menu.
- As you work through this list and complete tasks, the list of records will reduce for that day Eg: when you call and complete the initial health check it will be removed from this filtered list.

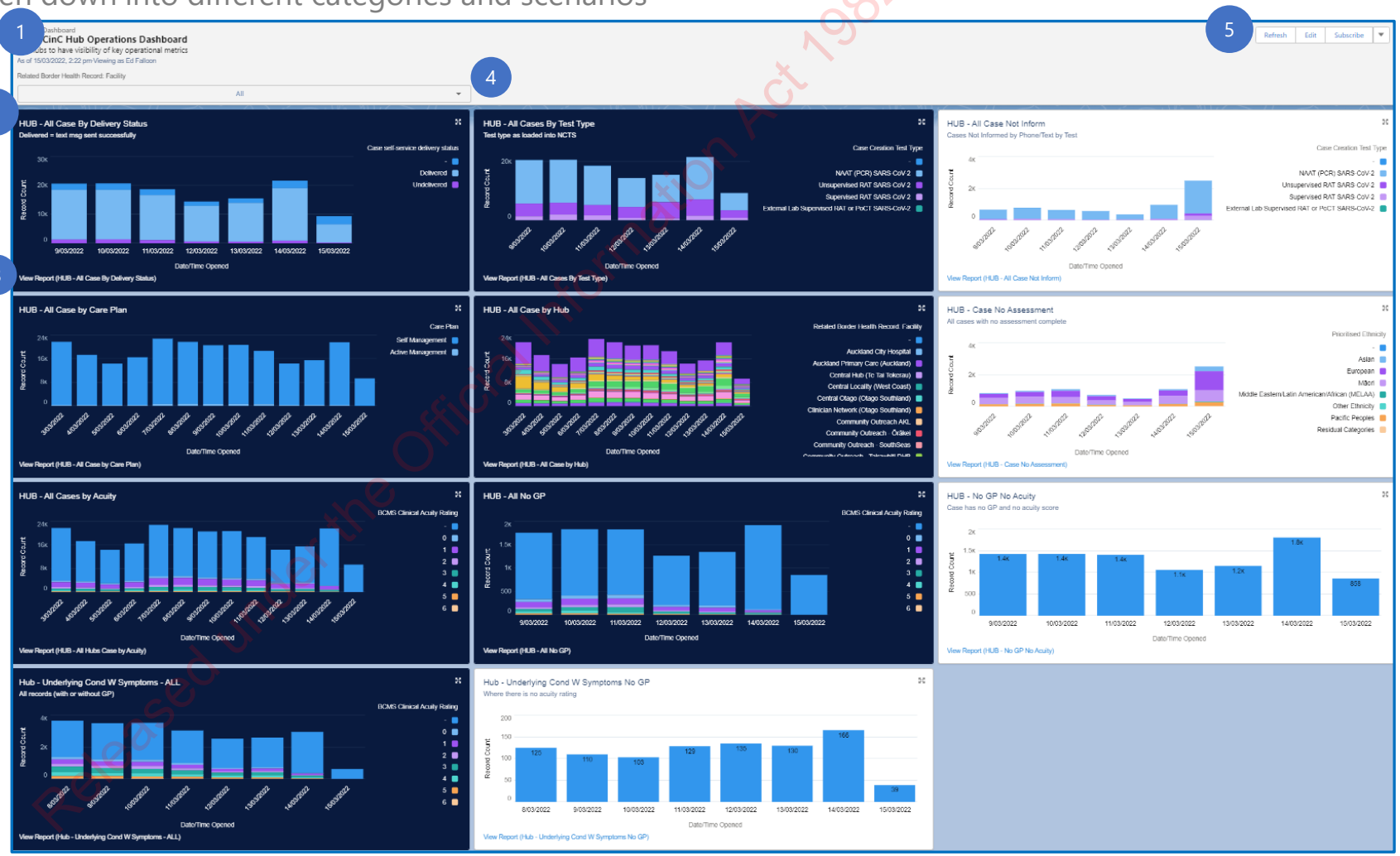
Dashboard | Landing page

Looking at the Dashboards components on the landing page is a great way to prioritise the workload in your team/Hub. Here you will see information specific to your hub broken down into different categories and scenarios

1. **Dashboard name** - This gives an indication of what the data set will tell us
2. **Components** – displays a different Report's data in an easy to manage graph
3. **Hyperlink** – this will open up the report and allow you to see more detail
4. **Filters –** options in this pick list allow you to see data specific to your hub or, as you can see here, all data in NZ
5. **Refresh** – Clicking this button will update every component to show real time information

Each component has been colour coded for your benefit:
Dark blue – gives you an overview of the data in your Hub
White – indicates the records that your Hub might want to look at more closely

Tip:
The next pages of this slide pack will deep dive into each report individually



NCTS Glossary | Key Terminology

Reports and Dashboards can help to organise your data and prioritise the work that needs to be done, here are some key terms that are common when using the report and dashboard function of NCTS

Record	Meaning
Risk Stratification Tool	The Risk Stratification tool uses information from the NHI data base to assign a number to each Case record in the NCTS. A patients age, prioritised ethnicity and vaccination status are calculated and issued a number between 0-1. The higher the number indicates the higher risk in regards to this patient and COVID 19. This number is not considered a clinical assessment
Risk Score	The Risk Score is a field attached to the back end of a Case record, it holds the number generated by the risk stratification tool. This field can be used in reports.
Reports	This is where you can view a specific set of data for multiple records at a time
• Folders	Folders can be public or private, if you can't see a report or don't have the permission to the private folder, you can ask for it to shared with you.
• Run	The data coming into the NCTS is always updating, you can click to Run a report to ensure that you are viewing the most current data possible
• Grouping	Sets of data can be grouped together in order to help view certain data sets, to make it easier to see and even sort the details in different ways
• Column header	The top of each column is the name of a filed in a record where the data is coming from. These can be sorted alphabetically or numerically, or rearranged from left to right along the report itself
Dashboard	Dashboards are a great way to visually display multiple reports and get a sense of the current workload
• Refresh	Remember to press the refresh button every time you look at a report, it doesn't always happen automatically so you need to trigger it to find the most recent data
• Components	Dashboards display a range of components, each component is a different report. The components are flexible and tailorable
• Underlying Conditions	These are details the are supplied from the Case themselves, either via the Self Serve Webform or with a phone call from a Contact Tracer in the PHU. This is a pick list in the NCTS

MINISTRY OF HEALTH
MANATŪ HAUORA

Risk Score for Call Prioritisation training (CCCM)

Training Guide

COVID-19 Care in the Community

Risk Score for Call Prioritisation

The COVID-19 Care in the Community team and the Data and Digital Directorate have developed a population-based risk stratification tool (the **Risk Score for Call Prioritisation**, or, **Risk Score** for short) that will be part of the COVID-19 digital platform when a positive case is identified.

- The tool helps to **identify** who needs to be **prioritised for contact** for the first assessment which determines whether their COVID-19 care needs to be supported with active care management or the self-service pathway.
- The tool will **support** Care Coordination Hubs by **prioritising outreach** from the hub to those who have not responded to the initial text outreach to indicate that they are positive for COVID-19.
- In this first version, the Risk Score **should not be used for clinical decision-making**. As we develop future versions the model, we will continue to undertake additional peer reviews to validate the model.
- The tool is a simplified model using **age, ethnicity and vaccination status data** to **inform risk of hospitalisation** due to COVID-19. This uses 0, 1 or 2 doses. Booster information will be included in future versions of the model. This model has been developed and evaluated using local data.

While the majority of people notified that they have COVID-19 will complete the online self-assessment tools which gathers information around co-morbidities and other health conditions, many people will not, leaving the Care Coordination Hubs unaware of the persons underlying conditions and current symptoms.

The **Risk Score** can be used here to sort and prioritise people for call back.

BCMS/CCCM Glossary | Key Terminology

Here are some key words that are common when using the dashboard function of BCMS

Record	Meaning
Risk Stratification Tool	The Risk Stratification tool uses information from the NHI data base to assign a number to each Case record in the NCTS. A patients age, prioritised ethnicity and vaccination status are calculated and issued a number between 0-1. The higher the number indicates the higher risk in regards to this patient and COVID 19. This number is not considered a clinical assessment
Risk Score	The Risk Score is a field attached to the back end of a Case record in the NCTS, it holds the number generated by the risk stratification tool. This number can be found in the Dashboard of CCCM
Dashboard	The Dashboard is available for those who have XX access in BCMS/CCCM, they are a great way to visually display multiple reports and get a sense of the current workload
• Sort By	These options will put the data in order of what column you choose from the sort by pick list. Ascending will put the lowest at the top of the page, Descending will put the highest at the top of the page
• Refresh	The refresh button will update the page with real time data, this can be useful if you have other people working in the same facility as you
• Search & Filter	The Search option will allow you to enter specific criteria then only show you records that meet that criteria. When you select a filter option it will narrow down your search again and only display the records that match that filter type. They can be used together or separately
• Reset All	This button in the Search and Filter pop up will remove any search or filter criteria that has been entered, it's a good option to use if you are managing different types of scenarios
• Reports	This is where you can view a specific set of data for multiple records at a time. Currently the reporting function sits with the NCTS system.