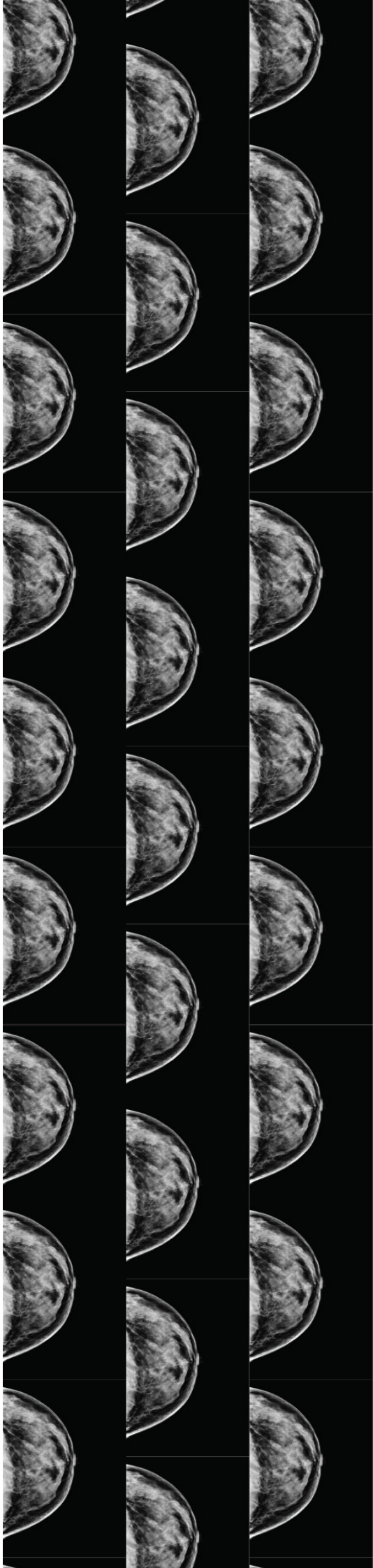
Capturing the benefits of AI in healthcare for Aotearoa New Zealand

A rapid report from the
Prime Minister's Chief Science Advisor
Kaitohutohu Mātanga Pūtaiao Matua ki te Pirimia

Full report

October 2023



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FOREWORD

Kia ora koutou,

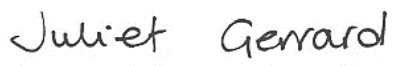
This report was requested by Prime Minister Hipkins in 2023 and was produced at pace for delivery of draft recommendations ahead of the 2023 election (full terms of reference outlined in Annex 1). With a focus on healthcare delivery, this report was produced with Ian Town, the Chief Science Advisor to Manatū Hauora | Ministry of Health and co-chair of our expert panel.

Employing AI technologies in healthcare has far-reaching impacts. There are ways in which these technologies could enhance the healthcare system very soon, for example improving back-office operations or diagnostic support. The case studies featured in this report offer a glimpse of current and near-future capabilities to start a conversation about how to introduce AI to our healthcare system.

Deploying the right AI technology has the potential to address some long-standing inequities in healthcare that will have positive impacts felt more widely than the healthcare system itself. Coupled with these opportunities are a series of complex ethical and legal issues. We understand that key health agencies are already planning work programmes which will go beyond the issues touched on in this report to ensure that AI is deployed effectively and safely in the health system. It is our hope that this report might support robust discussion amongst policy writers and decision makers to consider the best path to enable technology to support human care.

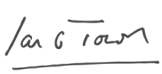
The successful deployment of AI into our healthcare system will depend not just on the technology itself, but on the wider healthcare system and system settings that are crucial to underpin smooth implementation. This necessitates a thorough understanding of our landscape at present (spanning legislation, policy, infrastructure, data, research, and workforce) coupled with a clear vision and cross-sector agreement for the future of healthcare. We recognise how rapidly the AI technology landscape is likely to evolve. As such, we have limited our recommendations to a timespan of five years, acknowledging there will be a need to re-evaluate both the AI and healthcare landscapes on an ongoing basis.

We thank our amazing expert panel whose experiences span healthcare, academia, technology development, ethics, philosophy, tikanga Māori and governance. We are also grateful to our reference group, which included academics, industry experts, entrepreneurs, and government agencies from both national and international settings. Finally a huge thank you to the writing team for putting the collected thoughts in order.



Professor Dame Juliet Gerrard FRSNZ HonFRSC

Prime Minister's Chief Science Advisor | Kaitohutohu Mātanga Pūtaiao Matua ki te Pirimia



Professor Ian Town FRACP

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ACKNOWLEDGMENTS

Our panel

We gratefully acknowledge the efforts of our panel whose expertise and guidance have shaped this report.

Dame Professor Juliet Gerrard (Co-Chair) - PMCSA

Professor Ian Town (Co-Chair) – Manatū Hauora | Ministry of Health

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Professor James Maclaurin – Te Whare Wānanga o Ōtākou | The University of Otago

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Megan Tapsell (*Ngāti Whakaue, Ngāti Pikiao, Ngāti Raukawa ki te Tonga*) – AI Forum NZ[i]

Dr Robyn Whittaker – Te Whatu Ora | Health New Zealand and Waipapa Taumata Rau | The University of Auckland[ii]

Professor Michael Witbrock – Waipapa Taumata Rau | The University of Auckland[iv]

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[i] Frontline diagnostics board member

[ii] Chair National AI & Algorithm Expert Advisory Group for Te Whatu Ora; Affiliated with the MedTech IQ Tāmaki/Te Tītoki Mataora Programme; Affiliated with Precision Driven Health

[iii] Working on a commercial contract with Soul Machines

[iv] Small stockholding in Volpara and Fisher & Paykel Healthcare

Our reference group

We thank the many academics, industry experts, entrepreneurs, and government agencies who formed our reference group. To those who met with the team, provided introductions, and generously contributed time, energy, and suggestions to this project, we are thankful for your contributions.

Though we have incorporated as much feedback as possible, not all suggestions were in agreement and not all could be incorporated. Our acknowledgement of people who helped us with this project in no way indicates their endorsement of the project itself. We have done our utmost to keep track of everyone who has contributed to this work. Please accept our sincere apologies for any inadvertent errors or omissions. Any mistakes in the report are our own.

AI Forum New Zealand | Te Kāhui Atamai Iahiko o Aotearoa

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Sarah Box

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Drew Broadely

David Brougham

Simon Brown

Ariane Chan

Kin Lung Chan

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Peter Chong

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Authors

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Juliet has held the position of Chief Science Advisor since July 2018. She has advised the Prime Minister on a broad range of subjects. She aims to create a trusted bridge between science, society, and government. She is also a Professor at Waipapa Taumata Rau | University of Auckland.

Professor Ian Town FRACP (Co-chair)

Ian is the Chief Science Advisor to the Ministry of Health. He has worked extensively on the development and implementation of the New Zealand Health Research Strategy and played a central role in New Zealand's COVID-19 pandemic response working with the PMCSA and the Director-General of Health to bring the latest evidence and research to decision-makers. More recently he has led the COVID-19 Vaccine Technical Advisory Group providing regular advice to the Director-General about vaccine strategy, efficacy, and safety.

Dr Rebecca Benson

Rebecca is a Senior Research and Policy Analyst. Her background is in quantitative social science, and she has worked at the intersection of research and policy at University College London, King's College London, and Queen Mary University of London. Rebecca earned her PhD in Public Policy at the University of Texas at Austin and has a Master of Public Health from Te Whare Wānanga o Ōtākou | University of Otago.

Dr Emma Brown

Emma is a Senior Research and Policy Analyst. Her background is in Engineering. Emma earned her PhD at Waipapa Taumata Rau | University of Auckland in the Chemical & Materials Engineering department.

Carolle Varughese

Carolle is a Research Analyst and Writer. Her background is in public policy, education, and physics. Carolle completed her Master of Public Policy at Waipapa Taumata Rau | University of Auckland, focusing on space policy in New Zealand.

VISION – PRIMARY HEALTH CARE IN AOTEAROA 2035

Jade is a GP in Newmarket and is part of a team practice in the heart of a bustling local community. At lunchtime one Wednesday, Jade calls her grandad to check how he is doing. He asks why she's not at work and laughs when she says she's on her lunch break. They didn't have lunch breaks in his day. He was a GP who retired early in the 2020s, completely burnt out. Her mum remembers the brutally long days he worked during the COVID-19 pandemic and the time it took to clear the backlog of non-urgent medical tasks and follow-ups afterwards. She spent a long time trying to persuade Jade to think of alternate career options. But thankfully, the workload is manageable for those in the health sector now. The smooth rollout of artificial intelligence support across the New Zealand public health system in the late 2020s completely changed the game. At the end of her medical training – which heavily utilised AI, preparing her for AI-supported practice – Jade was excited to be accepted into the GP training programme. This is now one of the most sought-after careers for graduating doctors who enjoy building relationships with their patients in local communities.

In this practice, Jade can access a full range of AI support modules. The basic ones are available throughout Aotearoa New Zealand, with all GPs trained to understand their role in human-centred medicine. The advanced modules are only available in hospitals or large practices in the major centres, with specialist training needed. So Jade also supports rural GPs and their patients remotely. In her practice, most patients arrive having already done a preliminary consultation with the personalised AI healthcare module on their phones. Biometric data is collected on a smartwatch, issued by the practice if the one they normally wear isn't compatible with the software. If patients have a particular condition or set of risks, specialist monitoring is set up in their home.

When Hēmi arrives for his appointment, Jade already knows that he has been having issues with his heart rate and blood pressure for some weeks now. The AI has suggested he call in because he has been working on his fitness and sometimes feels very faint after exercise. Jade logs into his file and sees what Hēmi has been told. He is a patient who has opted to receive quite a lot of technical detail as he is very health literate, but the system still has deeper information accessible to Jade. He definitely needs his medication adjusted, and the AI offers a range of possible treatments for Jade to discuss with Hēmi. This is a very efficient conversation, as he had already done some reading and made some preliminary decisions, and so the consultation is there to discuss these and provide some reassurance.

Jade adjusts the medication in the systems and alerts Hēmi's pharmacist to assess the dosage and any potential interactions by the time that Hēmi gets there. There is also time for Jade to ask some more general questions about his wellbeing, and how things are going in his life. Jade knows there are often additional important personal issues that people do not enter into their health record and prefer to discuss face to face. It turns out there are some stress factors that he can talk through with Jade, including his wife's health.

Hēmi's wife Ngahuia has been struggling with a wound on her big toe that won't heal. This is likely exacerbated by her diabetes, which Hēmi worries she is not managing well. While Hēmi is in the consultation with Jade, Ngahuia talks to Colin. Colin is one of the nurse practitioners at the practice

and provides patient support, teaching, and monitoring. Ngahuia and Hēmi had their appointments booked for the same time by the AI timetabling system, which was able to access both their schedules and those of the GP and nurse. This system seamlessly books their appointments to enable them to attend simultaneously. While assessing the integrity of the wound, Colin teaches Ngahuia to take care of the toe at home. Ngahuia indicated that she needed some reminders about what she learned, so Colin asks the clinic's AI assistant to send Ngahuia a virtual simulation about wound management around her big toe. He also chats with Ngahuia about her blood sugar management plan and her concerns about specialist monitoring of her wound at home. Unlike Hēmi, Ngahuia has been reluctant to adopt biometric data monitoring and sharing, so the only data available is from six monthly blood tests. Colin assures Ngahuia that she can receive care as she feels most comfortable. On the way home, she talks to Hēmi again about how his data-sharing supports his health and wonders whether she might trial using the data-sharing system in the future.

Hēmi is also pondering how widely to share his data. His heart issues are likely to include a genetic predisposition, and understanding the risk might be useful for his family. Jade took Hēmi through the options for sharing his data in the whānau-sharing system. Patients can opt in or out of the system, acknowledging that not everyone wants their siblings and cousins to know their medical history. Still, the data-sharing mechanism means that family members' GPs can be given general risk factors without any specifics, allowing treatment to be optimised for particular genetic risks without personal data being compromised. A similar iwi level data sharing system is also available which patients can opt in or out of. Hēmi decides whānau sharing is a good option for the health of his wider family. With all the basic data, scheduling, and diagnostics handled by the AI, there was more time to discuss the benefits and concerns of data-sharing. Hēmi doesn't go to the doctor very often, but when he does, he enjoys a trusting relationship.

Jade's next patient, Sheila, is concerned about her upcoming mammogram, especially after her mum tells her horror stories about the extent of breast compression during the procedure that she asserts are essential to get a good image. Jade explains that in the early days, it was indeed quite an uncomfortable experience, but the image analysis is now much more sophisticated and in three dimensions, which means that optimal compression is much less painful. The AI systems first introduced in the early 2020s are now much more sophisticated, and each mammogram is compared in detail to the patient's previous image, carefully separating natural changes in breast density from unexpected findings. Abnormalities can now be highlighted and assessed very quickly by an experienced radiologist, supported by AI. Jade takes time to talk Sheila through the process and explains how early detection means that very few women now suffer from advanced breast cancer. These days invasive biopsies are much less likely to be required, thanks to the sophistication that AI has brought to image analysis. She also talks Sheila through the protections in place for her children, whose data won't be shared beyond the immediate family until they are old enough to consent to this themselves.

Jade also offers Sheila the option for some genomic screening. The full set of genes associated with breast cancer is increasingly well understood. Sheila's family opted not to enable whānau-sharing with their personal data, but she can still opt to have her genetic information factored into her breast cancer health programme. It gives her a good handle on her personal risk factors and the optimal frequency of mammograms for her. Some women have mammograms every six months and others every five years, enabling the service to target those at highest risk.

Jade doesn't share the latest research findings because they are a long way from being implemented into clinical practice but is excited by the latest developments in precision medicine that were flagged in the news section of the AI diagnostic module. An early clinical trial on women with a particular mutation has just been carried out, showing that hormone replacement therapy which includes a specific inhibitor for one of the proteins that result from the mutation lowers the risk of specific breast and ovarian cancers. Jade is not expected to be able to keep up with the rapidly growing body of research; instead, the system provides her with a literature synthesis as well as recommendations and alerts.

Jade's next patient is new to the practice. Akshita has recently emigrated from the UK where the NHS offers much less advanced options than here in New Zealand. In an extended 30 min appointment, Jade explains how things work here and offers Akshita the option of having blood tests and a full medical exam to populate her baseline data in the system. She talks Akshita through how AI at the clinic can feed her personalised biometric data into the health system from a wristwatch in real-time. Jade emphasised that all data-sharing is strictly opt-in where personal health information can be used in tools that are approved for use in her clinical care, while de-identified aggregated data are used to directly inform the improvement of health services for all. Akshita is somewhat reassured that the data is tightly held for medical purposes only. Having generally low trust in the government, she goes away to think about which option she will take and the degree to which her data and AI will support the relationship with her GP. Jade showed Akshita the health system's AI chat tool in case she thought of any questions about her data and consent later. She is impressed that the AI can translate into any language.

Next up is Fred, who recently had a hip replacement and is here to discuss his rehabilitation. Although the operation was only a month ago, he seems very mobile as he enters Jade's office. Ahead of the operation, Fred had a series of scans, which gave the surgeon a precise understanding of the shape of his hip joint. The scans generated a blueprint for a bespoke 3D-printed implant that was seamlessly inserted during the operation using laser-guided robotic placement. Taking the guesswork out of the surgery significantly reduced the duration of the operation and the detrimental impact of the anaesthetic, making the surgery much better tolerated. Both Fred and Jade are excited about Fred's improved mobility, which has enabled him to start thinking about going for longer walks again and increasing his general fitness. Jade supports his idea of joining a community walking group, which will also improve his mental health. Fred was left alone since he lost his partner, and one of the worst impacts of his hip problems was reducing his social activity, triggering depression. Fred seems positive as he plans to reconnect with his mates.

Jade suggests that Fred check in with Colin about his health management. On chatting with Fred, Colin notices that he is getting a little forgetful in taking medication and installs a memory-jogging app on his watch. In fact, Colin uses a similar memory jogging app himself. His system prompts him to ask about the gap in Fred's biometric data due to him forgetting to put on his watch. Colin suggests an alternate memory-jogging system, which might make it easier to remember things. Fred already has a device providing an instant connection device to medical support on a screen near his bed, which he can access by pressing a button. Run by AI, the avatar on the screen knows Fred well, and they have a good relationship. It reminds him of basic daily tasks and automatically alerts the practice if there are any new concerns. Colin suggests they get the AI to remind Fred to put on his watch each morning.

The last patient of the day for Jade is a Telehealth appointment with Karen who lives on Great Barrier Island. Karen normally sees a local GP when she can afford to but has been referred to Jade before the GP drops by her place to assess whether she may have COVID-19. Karen is on home dialysis and has developed a nasty cough and a temperature over the last couple of days. Jade is trialling a new AI module that listens to a patient's voice and cough and gives a probability that the cough is indeed caused by COVID-19. There's a nasty new variant this year, so the health system is on alert. Karen chats to Jade, and the AI listens in and thinks there's an 85% chance it might be COVID-19—helpful information to relay to the local GP. Fortunately, predicting severe infection from COVID-19 (or other infectious diseases) and particularly the need for hospitalisation has become quite accurate over the last few years. Since performance measures are regularly and accessibly communicated to the public, their conversation reassures Karen. Jade knows that the local GP has undertaken the AI module on early detection of deterioration in patients with underlying health conditions like Karen. While there, Jade asks Karen if she'd like a retinal scan to confirm that her high blood pressure is being managed as well as checking for new problems such as diabetes. She agrees and puts her eye close to the camera on her phone, which is especially adapted for high-resolution retinal images. The AI runs a quick diagnostic, and everything looks in order, which is reassuring. Jade lets Karen know this, and her GP will be in touch later that day to deliver a COVID-19 test and give advice on the cough.

Before heading home, Jade asks the AI to run through the day, check all the notes, and alert her to any anomalies or omissions. She reviews her schedule the next day, and asks whether she should come in before 9 am to prepare for any appointments. One patient's file suggests a high uncertainty in the AI diagnostics, so Jade asks the AI to schedule 20 minutes for her to look at this ahead of time, and heads home to her family dinner with Grandad, confident that nothing is forgotten.

EXECUTIVE SUMMARY

In the wake of COVID-19, pressures on our health services and our healthcare professionals are immense and well-publicised. Though far from a panacea, artificial intelligence (AI) offers opportunities to strengthen the health system, support healthcare professionals, and improve the health of all New Zealanders. Taking a broad perspective of AI and its promise to improve health outcomes, we imagine an Aotearoa New Zealand in which the benefits of AI have been captured, at least in primary care, in our Vision.

The horizon of this rapid report is the near future, providing an overview of feasible opportunities within this time frame. We explored the possible benefits that AI may provide within the next five years and ways we can plan, manage, and deliver better outcomes in administrative areas, care delivery and health equity, population health and policy, and research. The report also features case studies from New Zealand and around the world to give a sense of the opportunities. Additionally, through the engagement process we were able to hear about the journey for some of our local case studies, and some of the hurdles they had to navigate are captured throughout the report.

In common with other countries, there are, of course, some challenging issues with which to engage as we adopt AI, including ethics, consent, governance, equity, and the risks of a digital divide. Our discussions also highlighted some themes unique to New Zealand such as digital infrastructure, nurturing data as taonga, population dynamics, and enabling access. We provide recommendations to help build an ecosystem that can fully capture the benefits of AI in the New Zealand health sector.

Principles

Drawing on the expertise of philosophers and ethicists on our expert panel, the 17 principles in this report sit within five themes.

Implementing Te Tiriti o Waitangi and recognising tikanga Māori

Globally, collective rights for Indigenous populations are recognised and affirmed by the United Nations Declaration of the Rights of Indigenous Peoples (UNDRIP). New Zealand gave its support to the declaration in 2010, acknowledging Māori as tangata whenua and affirming a commitment to the common objectives of the declaration and Te Tiriti o Waitangi.[i] Te Tiriti and its principles require consideration on an ongoing basis as the breadth of applications for AI in healthcare delivery continues to evolve.

[i] Te Tiriti o Waitangi is a founding document of government in Aotearoa New Zealand following the earlier signing of He Whakaputanga Rangatiratanga o Nu Tireni in 1835. The Waitangi Tribunal asserts that the sovereignty captured in the latter document was not erased or superseded by the drafting and signing of Te Tiriti.

Safe and effective AI

AI must be safe, not exposing patients to increased levels of risk. It must be effective in achieving the goals set out in the *Pae Ora | Healthy Futures Strategies 2023* to achieve health equity and improve health outcomes for all. This will require: the development of frameworks for assessment of AI in various healthcare contexts; better understanding of the limitations and risks of AI systems; and the development of rules and governance frameworks across the health system.

AI for equity

If we are to make good on the Pae Ora strategies, our deployment of AI must improve equity in access and in outcomes. There must be ongoing audit and evaluation of potential biases and prioritisation of use cases that enhance equity. While inappropriate use can lead to inequity, early evidence suggests that AI is capable of enhancing equity by lowering barriers to knowledge, reducing human bias's effect on care, enhancing access to healthcare, and increasing the productivity of healthcare professionals. If such productivity gains prove viable, it is essential that they be harnessed to increase the equity of healthcare provision.

Effective control of AI

Where AI is supervised by humans, it is essential that its supervision be effective. Increasingly, we will not always want to supervise all AI as confidence, capability, and trust builds. There will be low risk domains in which supervision is not cost effective and, as AI becomes increasingly powerful, we will be less competent at supervising it.

Evaluated and trusted AI

The use of AI in health contexts must be both trusted and trustworthy. People should understand the role that AI plays in their care. Significant effort is being put into explaining the nature and reliability of technology. But, by its nature, generative AI is less explainable. In some cases, its trustworthiness is best secured by effective and well communicated audit and evaluation, rather than by communicating the mechanics of its operation and the nature of the vast amount of data, sometimes sensitive, on which it is constructed.

Responsible AI

Effective use of AI requires clear rules about liability and responsibility.

Background

For this report, we use AI to mean technologies that simulate human intelligence: the ability to learn, reason, self-correct, and create new content. Importantly, although we are talking about the ability to mimic or augment human intelligence, there will be tasks where AI outperforms humans. We distinguish between predictive and generative AI at some points throughout the report as the technical, practical, or governance implications may differ:

- Predictive AI: systems that learn to map inputs onto outputs, through supervised learning, using training examples that illustrate the mapping

- Generative AI: systems that learn to generate or complete complex patterns (e.g., text or images), through exposure to large numbers of patterns during training

Adopting AI into the health system will require strong governance to ensure technologies benefit rather than harm our people and our health system. Examples of early governance structures are emerging. For example, within Te Whatu Ora| Health New Zealand, the National AI and Algorithm Expert Advisory Group (NAIAEAG) is responsible for reviewing proposals to develop or put into practice any new models of AI in our national health services. Various voices are represented within the advisory group including experts in AI, ethics, clinical, research, Māori health, data, digital, privacy, legal, and innovation. Proposals are considered against an assessment framework that considers various themes and perspectives.

Another emergent part of the governance structure is the *Therapeutic Products Act 2023*, which will come into force in 2026. The Act applies to some types of AI which will be considered 'software as a medical device'. Among other things, the Act enables a regulatory framework to require certain AI products used in healthcare to meet requirements for safety, quality, and performance. A regulatory body is being established and will provide market authorisation, licences, and permits for making software available. The criteria for authorisation are not yet established and will directly impact the effectiveness of the Act. This regulator, and the health governance system more generally, will need to balance various regulatory tensions. We hope this report is useful for their mahi.

The approach to governance of AI in healthcare in Aotearoa New Zealand will need to engage with Te Tiriti o Waitangi and relevant ethics frameworks. Kāhui Matatika o te Motu | National Ethics Advisory Committee provide ethical advice to the New Zealand health sector, and the World Health Organization has provided ethical guidance specific to the use of AI in healthcare. Lastly, the implications of the *Artificial intelligence and the Information Privacy Principles* set out by Te Mana Mātāpono Matatapu| Office of the Privacy Commissioner will provide a useful guide.

Addressing healthcare needs using AI

Existing AI technologies offer the possibility of improving the quality of care people are able to access in our health system while making the system itself more efficient. One of the low-hanging fruit in this regard is the automation of some of the administrative tasks that take up a lot of human resources. An example is scheduling an operation, where the rosters of several clinical staff and the availability of both a physical space and several specialised tools must be co-ordinated. Typing up notes and routine communications with patients are other administrative tasks where AI could reduce the time spent by humans.

Computer vision – which refers to machine perception of visual images – is a field with many applications that can augment clinical judgment, resulting in more accurate diagnoses and treatment, and faster provision of results to patients. Medical images are commonly used in healthcare to identify problems or abnormalities: X-rays, CT, MRI, and mammograms produce visual representations for interpretation by radiographers; gastroenterologists use endoscopies and colonoscopies to image our digestive tracts; dermatologists examine our skin for abnormalities; and allied health professionals examine microscope images. In all these cases, clinicians are using their training and experience to interpret what they see, and they don't always get it right. AI tools can be

trained to examine these images and in the right circumstances can be more accurate than humans, and take less time. Augmenting human judgment with AI may result in faster and more accurate results from many types of medical imaging.

Another example of the opportunities AI can offer to the health sector is in the field of biomedical research. At present, this is best exemplified by Alphafold, a tool which can accurately predict the folded structure of a protein from the sequence of amino acids. This allows scientists to predict the protein's function, enabling more rapid drug development with obvious implications for the health sector.

One of the main reasons to explore the use of AI in the health sector is the potential for very high return on investment. In a sector with staff shortages and limited funding, tools that can achieve high levels of health improvement and/or remove some of the most burdensome tasks undertaken by human resources can make meaningful differences to what can be achieved. In order to realise this return on investment, any AI tools adopted must be evaluated to ensure they meet the needs of the sector and health system users.

Considerations for our Aotearoa New Zealand context

Te Tiriti o Waitangi requires Crown must protect the rights and interests of Māori and to govern in partnership with tangata whenua. Adoption of AI in the health sector must give effect to te Tiriti, by, among other things, partnering with Māori in its implementation and recognising that Māori data are taonga. This view is reinforced by supranational organisations, namely the United Nations in its Declaration on the Rights of Indigenous People. The health sector has acknowledged the Hauora report finding that health disparities experienced by Māori are violations of Te Tiriti.

As a new technology, AI has the potential to provoke scepticism and fear. If clinicians and the public are distrustful of AI, it is unlikely to maintain social license and we risk not being able to realise the benefits of its use in the health sector. International data suggests that New Zealanders tend to be less positive about AI than others globally. However, local research suggests that when using our data to build AI healthcare tools, we tend to be positive about the opportunity to 'give back', as long as there are sufficient assurances around data security. We are not aware of any studies of New Zealand clinicians' trust in AI, but international evidence suggests that an effective communications strategy clearly articulating the evidence-based benefits clinicians can expect through the use of AI technology is likely to be useful. More broadly, it is likely that the AI literacy of the public, clinicians, and those tasked with making decisions about AI adoption, will need to be improved. Along with including AI in medical education, improving the wider public understanding of AI may also be helpful in increasing trust.

An important consideration in adopting new technologies is health inequities: differences in health that are avoidable and unjust. In its Pae Ora strategies, Manatū Hauora has laid out its vision for an equitable health system, with specific strategies for priority groups[i] who are underserved by the

[i] The priority groups identified by Manatū Hauora are by no means the only communities who experience inequity in accessing healthcare, nor are they the only groups for whom AI can improve health access. The possibilities for AI to improve equity in health access by making decisions free of human bias, identifying patterns of unequal treatment, and providing new modes of care delivery can benefit all these groups.

status quo: Māori, Pacific people, people with disabilities, rural people, and women. Manatū Hauora has developed distinct health strategies for each of these groups, but for our purposes thinking about the ways in which AI could address or exacerbate inequalities, these categories often intersect and compound disadvantage, and any AI tools aiming to reduce inequity would ideally address intersectional disadvantage.

Although AI is unlikely to address the structural causes of health inequities, there is great potential for it to impact on some of the proximate causes. To the degree that AI is more accurate in diagnosis and treatment, groups who systematically experience worse accuracy in current practice are likely to benefit. AI could also lead to fairer allocation of resources, and remove some barriers to accessing healthcare that lead to health inequities. We do know that AI technologies are prone to reflect, and may amplify, human bias and discrimination, but with appropriate mitigation like monitoring for signs of bias, we can ensure that adoption of AI monitors bias and improves health equity.

Where to from here?

The development, deployment, and adoption of AI within the healthcare sector requires robust dialogue at a systems level to create an enabling ecosystem. Indeed, the impact of AI will depend on more than just the technical capability of the tools. The wider AI ecosystem, spanning regulatory settings, the talent pipeline, commercial incentives, data repositories and governance bodies are all crucial aspects that will impact on the health sector's ability to benefit from emerging technology. Ensuring strong relationships between actors in the public sector, privacy sector, relevant agencies, research institutions, health system, and consumer groups will provide useful support to inform the evolving AI and healthcare landscape.

Recommendations

This report makes 22 recommendations made in this report that are grouped within eight major themes. These themes are summarised here, while our specific recommendations highlight where some of the work could be carried out and provide suggestions on levers that might support this work.

Mapping the landscape in Aotearoa New Zealand

Many aspects of the healthcare landscape will evolve with the ongoing deployment of AI in healthcare delivery in New Zealand. Examples include back-office efficiency, image analysis, research, and technology development. It is important to maintain an awareness of the needs and opportunities within our national context.

Maintaining the human element of care

While there are clear opportunities for improvements in efficiency and data processing, the extent to which AI systems might augment our current healthcare service delivery is unclear. Establishing an understanding of the crucial human elements of healthcare delivery will support decision-makers to deploy AI technologies in the appropriate supporting areas.

Enabling adoption

Adopting AI systems into our healthcare system will not happen on its own, but needs the appropriate policy settings, educational provision, and funding to enable effective adoption of AI technology that will support improved health outcomes for New Zealand.

Establishing confidence and trust

Establishing a sense of confidence and trust in AI technology is important. Effective engagement with the public, various tiers of the healthcare workforce, and those in research and development fields will help to build confidence. Clear understanding of AI limitations and associated risks, coupled with the appropriate frameworks for assessment and governance will support establishment and maintenance of confidence and trust across the healthcare sector.

Tackling inequity

The adoption of AI in healthcare should not just replicate our current health outcomes. We can ensure that AI technology facilitates better outcomes for everyone in New Zealand. This necessitates developing an understanding of where our greatest health needs are and ensuring that we deploy the technologies most suitable for closing equity gaps.

Te ao Māori

Unique to the Aotearoa New Zealand context is Te Tiriti o Waitangi. Relevant iwi, hapū, whānau and Māori organisations should be included in decision-making processes as partners alongside the Crown. Partnership should be evident throughout all stages of project life-cycles spanning conception, planning, governance, design, and implementation.

Data and systems

We cannot talk about AI without also talking about data and inference. Implementation of AI technologies within our healthcare system requires inference from large data sets. This raises issues about data collection, data privacy, data sovereignty and cyber security, and about the safety, reliability, and effectiveness of the inference this data enables.

Exploring future opportunities

AI introduces various opportunities to improve outcomes in our healthcare system. Our investment choices can create the right environments to foster research and innovation that enable us to take advantage of new and exciting opportunities.

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1. DEFINITIONS

We begin by providing definitions for predictive and generative AI as they are used in this report. The distinction between the two types of AI systems is broad, informal, and certainly not exhaustive, however we emphasise these definitions specifically as their meaning plays a significant role in structuring the discussion about AI in healthcare at several points in this report. Additional definitions for terminology throughout the report are captured in the glossary.

Predictive AI

A 'predictive' AI system learns to map inputs onto outputs, through supervised learning, using training examples that illustrate the mapping. Training examples are typically defined by human experts, and often require considerable effort (money and time) to assemble. Predictive systems can use many different learning methods, ranging from well-established statistical techniques that have been in use for many years (such as linear regression), to more complex modern AI methods (such as deep neural networks). But while they use a range of different learning methods, they can all be evaluated in the same basic way: by examining the performance of a trained model on a 'test set' of examples. In evaluation, the systems' predictions are compared with a gold standard – a human expert, or, better, the known status on a relevant clinical endpoint – and the result is reported as a percentage accuracy score. The newer and more complex predictive systems often outperform the older statistical systems on accuracy. But there is a trade-off: the most complex systems are often the ones whose decisions are hardest to explain to a human user. The best performing predictive models tend to function as 'black boxes', whose decision-making processes are impenetrable to human observers. Large neural network models are archetypal 'black boxes'.

Generative AI

A 'generative' AI system learns to generate or complete complex patterns (e.g., text or images), through exposure to large numbers of patterns during training. The recent interest in AI is largely due to consumer-facing generative AI systems: for instance, ChatGPT is a generative system that produces text; MidJourney is a generative system that produces images. 'Multimodal' generative AI systems are also being developed, that learn about associations between text and images. Other modalities are also being incorporated, in systems that can handle audio and video stimuli, or that can generate motor outputs that control robots. Generative AI systems rely heavily on complex neural network models of various kinds. They typically need less human involvement during training: much of their learning happens through 'self-supervision'. For example, ChatGPT learns to predict the next word in its training texts - a measure on which it can 'test itself'. Users interact with a trained generative AI system by providing a 'prompt' - for instance, a piece of text, or an image, or some mixture of these - which the system then responds to by extending the text, or completing the image, based on the regularities it has learned during training. This mode of interaction allows users to integrate generative AI systems into an open-ended variety of real-world tasks - in which they have shown an ability to produce surprisingly natural or human-like responses. These abilities have catapulted them into the public eye. At the same time, we do not yet have established ways of evaluating the performance of generative AI systems in real-world tasks. The systems themselves are too new, and we don't yet fully understand how they achieve their humanlike responses. Sometimes they generate credible responses that are wrong. (Again, these systems are archetypal 'black boxes'.) Real-world tasks are complex and open-ended, which also complicates evaluation.

Glossary

We introduce terms here that are used throughout the report. While some of the terms included are relatively non-technical, the intent is to ensure that readers from various backgrounds are able to engage with the contents of the report.

Black box	A system whose outputs are produced through mechanisms that are hard to understand because of their complexity or because the code or logic used are unknown to users and sometimes to developers.
Bias	There are different types of biases, however we refer to systematic patterns of output from AI and algorithms which unfairly disadvantage individuals or groups. Bias can arise through poor quality data, particularly selection effects and confounding, or from human factors in algorithm design and/or deployment.
Deep learning	A subset of machine learning that uses many layers of neural networks to produce an output. A deep network, properly trained, can learn its own representations of inputs, in its internal 'hidden layers'.
Digital twin	A digital representation of an object, a person, or an environment that is used as a counterfactual for simulation, modelling, or representing processes.
Hallucination	An incorrect statement presented as fact by a generative AI model – most commonly, a large language model.
Large Language Model	A large neural network model designed to learn the structure of language (or more generally, any training data that is arranged into sequences). During training, models learn to predict words from their surrounding context. After training, given a 'prompt'—a piece of linguistic context supplied by the user—models can produce a humanlike response, by iteratively predicting 'the next word'. Large language models are distinguished by their enormous size, and by the huge amounts of data they are typically trained on.
Machine learning	Techniques that allow machines to learn generalisations from data in order to make predictions or decisions.
Natural Language Processing	A field focused on machines' ability to interact with humans by understanding and processing text or speech from human languages.

Neural networks	Algorithms that are modelled on biological neurons in the brain, having multiple interconnected nodes through which information flows. Learning in a neural network involves changing the ‘weights' of these connections, to change how information flows between units.
Prompt engineering	A new discipline that has arisen since the advent of large language models. Users interact with a large language model by providing it with ‘prompts', that indicate the nature of the text it should produce. These prompts can be elaborate, to indicate in detail what kind of output is required. Many heuristic methods for structuring prompts to guide the system's output are being learned; prompt engineering is the application of these methods to optimise outputs from generative AI interfaces.
Human supervision	The use of humans in overseeing the inputs, outputs, and processes that the AI performs after it is deployed. Not to be confused with supervised learning, which occurs during training.
Supervised learning	A category of machine learning where algorithms have been trained on data that has been labelled by humans.
Training	A process in which a model ingests data and learns to recognise patterns within the data. This process can be supervised or unsupervised.
Transformer	A neural network model with a specific architecture that allows the model to understand relationships between all data elements in a sequence, even if they are distant from each other. This enables translation, understanding of context, and generation of new content in fluid way, as exemplified by ChatGPT.
Unsupervised learning	A category of machine learning where algorithms have unlabelled data and requires pattern seeking.

Abbreviations

DALY	Disability Adjusted Life Year
FDA	Food & Drug Administration (US)
FL	Federated Learning
GPT	Generative Pre-trained Transformer
IMDRF	International Medical Device Regulators Forum
LLM	Large Language Model
NAIAEAG	National AI & Algorithm Expert Advisory Group
NLP	Natural Language Processing
OPC	Office of the Privacy Commissioner
QALY	Quality Adjusted Life Year
ROI	Return on investment
SaMD	Software as a Medical Device
TGA	Therapeutic Goods Act (Australia)
TPA	Therapeutic Products Act (New Zealand)
UNDRIP	United Nations Declaration on the Rights of Indigenous Peoples
WHO	World Health Organization

2. PRINCIPLES

The frameworks and challenges of ethics around AI in healthcare presented in this report are important background, but do not provide clear guidance for policy makers on their own. Our panellists, Professor James Maclaurin and Dr Karaitiana Taiuru, articulated principles for using predictive and generative AI in Aotearoa New Zealand. Given the rate of progress in the development of AI, principles should be revisited annually or as often as seen fit by relevant authorities. The principles may be useful for developers, medical professionals, patients, users, and regulators. We acknowledge that some principles create tensions. These are helpful to frame policy choices.

A. Implementing Te Tiriti o Waitangi and recognising tikanga Māori

Globally, collective rights for Indigenous populations are recognised and affirmed by the United Nations Declaration of the Rights of Indigenous Peoples (UNDRIP). New Zealand gave its support to the declaration in 2010, acknowledging Māori as tangata whenua and affirming a commitment to the common objectives of the declaration and Te Tiriti o Waitangi. Te Tiriti and its principles require consideration on an ongoing basis as the breadth of applications for AI in healthcare delivery continues to evolve.

Principle 1

Mana whakahaere: effective and appropriate stewardship or kaitiakitanga over AI health systems recognises Māori data are a taonga and subject to Māori data sovereignty principles determined by Te Tiriti. This includes individual and collective rights with whānau, hapū, iwi, and Māori organisations.

Principle 2

All AI systems will embed Māori leadership, decision-making, and governance at all levels of the systems life-cycle spanning inception, design, release and monitoring.

Principle 3

Mana motuhake: Enabling the right for Māori to be Māori (Māori self-determination); to exercise authority over their lives, and to live on Māori terms and according to Māori philosophies, values and practices which are framed by te ao Māori (the Māori world), enacted through tikanga Māori (Māori philosophy & customary practices) and encapsulated within mātauranga Māori (Māori knowledge).

Principle 4

Mana tangata: AI systems will support equity in health and disability outcomes for Māori (individuals and collectively) across their life course and contribute to Māori wellness.

B. Safe and effective AI

AI must be safe, not exposing patients to increased levels of risk. It must be effective in achieving the goals set out in the *Pae Ora|Healthy Futures Strategies 2023* to achieve health equity and improve health outcomes for all. This will require: the development of frameworks for assessment of AI in various healthcare contexts; better understanding of the limitations and risks of AI systems; and the development of rules and governance frameworks across the health system.

Principle 5

Health delivery entities must have policies regulating the use of AI.[i] Such policies should specify an assessment process for AI tools to go through before use and an ongoing evaluation process for accuracy, efficacy and safety, addressing issues such as ease of use, bias, security, and data sovereignty.

Principle 6

Assessments of AI for use in healthcare should be made with an opportunities lens, making comparisons between the performance and reduction of mental and physical harm of AI and alternatives available within the Aotearoa New Zealand health system.

C. AI for equity

If we are to make good on Pae Ora, our deployment of AI must focus on enhancing equity in access and in outcomes. There must be ongoing audits and evaluation of potential biases and prioritisation of use cases that enhance equity. While inappropriate use can lead to inequity, [1] early evidence suggests that AI is capable of enhancing equity by lowering barriers to knowledge, monitoring human bias, enhancing access to healthcare, [2] and increasing the productivity of healthcare professionals. [3] If such productivity gains prove viable, it is essential that they be harnessed to increase the equity of healthcare provision.

Principle 7

AI tools should be designed and implemented to address health inequities, by prioritising the health needs of disadvantaged groups including those identified as priority groups by Manatū Hauora and other groups as appropriate.

Principle 8

All use of AI should be subject to ongoing audit and evaluation for bias.

[i] Manatū Hauora| Ministry of Health has the Health Information Governance Guidelines and other entities will need to adapt or develop their own policies

Principle 9

The permissibility of AI use should be judged relative to the actual healthcare that individuals are likely to receive, not to an ideal level of treatment and support.

D. Effective control of AI

Where AI is supervised by humans, it is essential that its supervision be effective. [4] Increasingly, we will not always want to supervise all AI as confidence, capability, and trust builds. There will be low risk domains in which supervision is not cost effective and, as AI becomes increasingly powerful, we will be less competent at supervising it. [5]

Principle 10

Where AI is supervised:

a) All AI-generated information relevant to treatment must be independently checked before it is acted on
b) Supervisors must be competent to make the decisions that we are asking AI to make, i.e., the operation of an AI must be within the scope of practice of those tasked with its supervision
c) Everyone who uses AI in a clinical setting should be trained in its use, for example, the circumstances in which a given AI tool is likely to be more and less accurate, and in relevant principles of prompt engineering

AI may be used unsupervised where:

d) The use is low-risk and its performance is subject to ongoing audit and evaluation showing that it increases accuracy, equity, or patient satisfaction or that it decreases cost without sacrificing accuracy, equity, or patient satisfaction

Or

e) The use is medium-risk and its performance is subject to ongoing audit showing that it is demonstrably more accurate and/or unbiased than the human decision-makers it is replacing

E. Evaluated and trusted AI

The use of AI in health contexts must be both trusted and trustworthy. People should understand the role that AI plays in their care. Significant effort is being put into explaining the nature and reliability of technology. [6] But, by its nature, generative AI is less explainable. In some cases, its trustworthiness is best secured by effective and well communicated audit and evaluation rather than by communicating the mechanics of its operation and the nature of the vast amount of data, sometimes sensitive, on which it is constructed.

Principle 11

The trustworthiness of predictive AI should continue to be secured by using relevant and representative training data, maintaining transparency, and retaining human oversight (as construed by the most up to date guidance for our national context such as the *Principles for Safe, and Effective use of Data and Analytics*[7,8] jointly developed by Te Mana Mātāpono Matatapu | Privacy Commissioner and Tatauranga Aotearoa | Stats NZ, and *Artificial intelligence and the Information Privacy Principles*[8] set out by the Privacy Commissioner).

Principle 12

The trustworthiness of generative AI should be underpinned by ongoing well-communicated audit and evaluation. Such audit should address accuracy, bias, fitness for purpose, privacy, data security, and data sovereignty.

Principle 13

Aotearoa New Zealand should explore methods for mitigating bias and for securing data sovereignty, particularly Māori data sovereignty. These might include the development of generative AI in New Zealand which either stands alone or works with commercial AI based in other countries. Health data of people in New Zealand must not be collected, defined, stored, or processed in systems that are not subject to New Zealand law.

Principle 14

New Zealand should develop a strategy to widely communicate the benefits and risks of the public using generative AI as an alternative to consulting healthcare professionals.

F. Responsible AI

Effective use of AI requires clear rules about liability and responsibility.

Principle 15

The use of AI as a 'practitioner co-pilot' can be mandated in domains in which its performance is subject to ongoing audit and evaluation showing that it is more accurate and no more biased than human decision-makers.

Principle 16

Health organisations are responsible for decision-making (as per principle 5) about the purchase, provisioning, audit, evaluation, and authorisation of AI systems.

Principle 17

Practitioners supervising AI are responsible for its operation and they remain liable for decisions made using AI generated advice, and for meeting requirements of the *Health Practitioners Competence Assurance Act 2003*.

3. RECOMMENDATIONS

Guided by our panel of experts, we have developed 22 recommendations grouped within eight themes. The themes are summarised here and are not listed in any particular order of importance. The recommendations highlight where some of the work could be carried out and specific considerations that might be of interest for decision makers and policy writers.

Mapping the landscape in Aotearoa New Zealand

Maintaining the human element of care

Enabling adoption

Establishing confidence and trust

Tackling inequity

Te ao Māori

Data and systems

Exploring future opportunities

Theme 1: Mapping the landscape in Aotearoa New Zealand

There are many aspects of the healthcare landscape that will evolve with the ongoing deployment of AI in healthcare delivery. Examples include back-office efficiency, image analysis, research, and technology development. It is important to maintain an awareness of the needs and opportunities within our national context.

R1: Assess the various needs in clinical settings that can be addressed by AI

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations:
a) Canvas national healthcare settings to ensure that the various needs (i.e., staff, individual patient, whānau, and community) are understood. This could: i) Highlight local, regional, and national needs to identify and prioritise the appropriate deployment of AI healthcare interventions ii) Be utilised to inform research and development efforts b) Ensure ongoing horizon scanning to maintain an awareness of emerging technologies in AI and healthcare and the extent to which needs in clinical settings might be addressed	c) Monitor and evaluate evolving healthcare needs across settings. This could: i) Support the identification of areas for future deployment ii) Enable New Zealand to lead developments in areas of particular priority to our national healthcare needs	• R1:a could be undertaken jointly by agencies such as: ○ Manatū Hauora | The Ministry of Health ○ Te Whatu Ora | Health New Zealand ○ Te Aka Whai Ora | Māori Health Authority ○ The regulatory body established for oversight of the *Therapeutic Products Act 2023 (TPA)* [i]

[i] https://www.legislation.govt.nz/act/public/2023/0037/latest/DLM6914502.html?src=qs

R2: Understand the impact of our legislative settings on the development and deployment of AI for healthcare delivery in New Zealand

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Review current policy and legislative settings to understand their impact on research, development, and implementation of AI systems within healthcare settings in New Zealand. This should: i) Highlight enablers and barriers for the deployment of AI in healthcare settings (both public and private) ii) Identify policy/legislation for review b) Develop an understanding of various capabilities of AI technologies and develop a robust framework to support appropriate regulation. This could: i) Distinguish AI technologies according to type and output (for example, operational efficiency improvements compared to self-learning AI and diagnostic support) and establish the extent to which regulations are required for distinct applications ii) Ensure independent testing requirements for the evaluation of impact and safety	c) Assess whether the evolving AI in healthcare landscape is appropriately supported by legislative settings d) Ensuring ongoing monitoring of relevant safety signals, performance, and quality of AI-enabled technologies e) Continuous horizon scanning to maintain awareness of AI-enabling technologies (e.g., quantum computing, VR, etc) to inform regulatory settings	• R2:b could be led by Manatū Hauora with support from other relevant agencies such as Te Whatu Ora and Te Aka Whai Ora • For R2:b, where AI applications are already well understood and evaluation mechanisms well established, regulation should promote best practice(s). Where there is not yet a well-established best practice for evaluation of particular AI tools, regulation should limit adoption until such a time that evaluation best practice is well established • R2 should take into consideration principles 5, 10 and 15 • There should be ongoing monitoring of rules and regulations established to support the TPA and the implications for AI in healthcare

R3: Understand the distribution of capabilities across the public and private sectors

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Complete scan to understand current and potential public and private capabilities that will inform longer term resource and capability planning. This should highlight where specific AI healthcare expertise sits within our current NZ ecosystem	b) Monitor and evaluate research and development findings from relevant institutions and the extent to which developments have supported aspirational mid-to-long term goals c) Evaluate public and private capabilities to determine: i) Potential opportunities to collaborate across public and private settings ii) The extent to which capabilities should be enhanced to close potential gaps in healthcare needs specific to New Zealand iii) The size of the technical workforce to conduct evaluation and authorisation of new AI-enabled technologies	• R3:c (iii) The Therapeutics Products Regulator could require appropriately trained staff to effectively evaluate and regulate relevant technologies

R4: Understand the national AI research and development landscape for healthcare

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Identify current national AI and healthcare research capabilities across universities and CRIs. This could: i) Provide clarity around research and development outputs from New Zealand that have the potential to be implemented in our healthcare industry ii) Provide short-to-medium term clarity around future research needs for New Zealand and our research partners	d) Monitor and evaluate research and development outputs from relevant institutions and the extent to which developments have proven safe, effective, and equitable in clinical settings e) Evaluate research findings and establish future AI research needs f) Evaluate computing capabilities and appropriateness for future demands	• R4:a could be undertaken by various agencies/institutions including but not limited to: ○ Manatū Hauora ○ Te Whatu Ora ○ Te Aka Whai Ora ○ Hīkina Whakatutuki | Ministry of Business, Innovation & Employment (MBIE) ○ Universities

iii) Provide clarity on tertiary AI courses available across institutions iv) Support the establishment of aspirational mid-to-long term goals for healthcare delivery in New Zealand and related research and development b) Undertake regular horizon scanning to establish an understanding of future potential areas for research & development c) Understand enablers and barriers experienced by technology developers in the AI healthcare sector. This should: i) Be used to inform the ongoing development of suitable legislative settings ii) Inform discussion around support tools/services that might help to reduce complexities		○ Research institutions/organisations • Mapping of national capabilities could highlight areas where Aotearoa New Zealand might have a competitive advantage in AI healthcare. This might look like a database that is regularly updated with details of AI and healthcare related research in New Zealand and could be undertaken by an agency such as MBIE • Mapping of national capabilities should be undertaken alongside R1 to ensure we are developing expertise that is guided by our healthcare needs • R4:a,b and d should consider resourcing and leadership capabilities for research and development of AI for healthcare delivery. • R4:b should be undertaken in conjunction with R5:b

R5: Understand the international AI research and development landscape for healthcare

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Identify international AI and healthcare research capabilities across jurisdictions. This could provide short-to-medium term clarity around potential collaborative efforts and/or key partnerships to be	c) Monitor and evaluate research and development, and regulatory outputs across jurisdictions (for example, Therapeutic Goods Administration (TGA) in Australia)[i]	• R5:a could be undertaken by various agencies/institutions including but not limited to: ○ MBIE ○ Universities

[i] https://www.tga.gov.au/

established across government agencies and research institutions b) Undertake regular horizon scanning to establish an understanding of future potential areas for research & development		• R5:b should be undertaken in conjunction with R4:b

Theme 2: Maintaining the human element of care

While there are clear opportunities for improvements in efficiency and data processing, the extent to which AI systems might augment our current healthcare service delivery is unclear. Establishing an understanding of the crucial human elements of healthcare delivery will support decision makers to deploy AI technologies in the appropriate supporting areas.

R6: Ensure relevant targeted information is available for decision makers at all levels of the healthcare system

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Understand comfort levels of healthcare staff and the public about the use of AI in healthcare delivery. This work should: i) Canvas a diverse range of voices within the community ii) Inform governance bodies and decision makers of the healthcare desires and levels of comfort within their respective communities distinguished by application. For example, patients may be fine with an AI scheduling system but might prefer to know if AI has been used in image diagnosis iii) Identify the factors that contribute to comfort levels	d) Understand evolving trust levels of healthcare staff and the public around the use of AI in healthcare delivery. This work should: i) Capture any changing attitudes among the public as trust in AI technology is built ii) Identify factors that contribute to changing attitudes iii) Inform decision makers of levels of comfort within communities and likely future needs	• R6 should take into consideration principles 5,12,14,15,17 • Those in governance and decision-making roles should maintain awareness of developments in AI to ensure decisions are informed by the most relevant and up-to-date information

iv) Identify at what stage of receiving healthcare that patients desire to know that AI has been used b) Understand experiences of AI technology developers around the development and deployment of AI for healthcare in New Zealand. This work should: i) Canvas a diverse range of technology applications ii) Inform governance bodies and decision makers of developers experiences and the extent to which New Zealand is a desirable market to partner with c) Understand the ongoing interactions between clinicians and AI and healthcare delivery		

R7: Develop an understanding of crucial human elements of healthcare delivery

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Distinguish different types of AI technologies and their capabilities to assist, augment or replace the human element of patient interaction. This should: i) Inform decision-making around the deployment of AI technologies across healthcare settings ii) Inform the development of evaluation, deployment, and supervision criteria b) Identify tasks (both clinical and administrative) where deployment of AI might safely free up the time of healthcare professionals and ensure that default	d) Maintain an awareness of emerging AI applications to enhance healthcare delivery by augmenting and/or replacing humans to free up time for healthcare professionals to carry out higher priority work	• R7 should take into consideration principles 8, 10, 14, 15 and 17 • R7:a should be considered alongside feedback from R6:a

settings allow for the most efficient process in any given context. (Examples include, but are not limited to, high-volume/repetitive tasks such as scheduling appointments or sending reminders) c) Identify and distinguish AI technologies that will require supervision in clinical settings from those that will not		

Theme 3: Enabling adoption

Adopting AI into our healthcare system will not happen on its own. The appropriate policy settings, targeted information provisions, and resourcing to enable effective adoption of AI technology that will support improved health outcomes for Aotearoa New Zealand will be key to seeing effective outcomes.

R8: Establish guiding principles and practices for adoption of AI in our healthcare settings

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Establish and/or adopt guiding AI principles appropriate for Manatū Hauora, Te Whatu Ora and Te Aka Whai Ora, and consistent with strategic national objectives (example Principles are included in this report) b) Ensure that healthcare workforce are adequately informed to understand newly adopted guiding principles for AI in healthcare settings c) Identify resources required for implementation of best AI practice across the health system d) Establish and/or adopt formal evaluation processes for pre- and post-	g) Re-evaluate principles and evaluation processes h) Technologies with post implementation evaluations that demonstrate clear efficiency improvements should be adopted more broadly as standard practice i) Automation should become default practice unless there is compelling reason not to ii) Evaluation for widespread adoption and standard practice should establish the extent to which successful technologies are	• The establishment of guiding principles and practices for the adoption of AI will also be key to establishing confidence and trust in the healthcare system. As such R8 should be factored into the communications strategy outlined in R10 • R8:e could be undertaken by various agencies including but not limited to: ○ Te Whatu Ora ○ The TPA regulatory body • R8:f(iv) could be informed by evaluation outcomes from R8:d • R8:f will need to be informed by legal framework for enforceable product standards

implementation of new AI health technology. Evaluation processes should: i) Take into consideration best evaluation practice for the technology in question (if best practice has been established) ii) Take into consideration system resourcing and the extent to which AI technologies are compatible with existing resources (for example if AI tools are more efficient at screening for breast cancers, is the system adequately resourced to cope with increased detection) iii) Where best practice for evaluation has not been established, the technology should be limited in its application with sufficient mechanisms to prevent use on an experimental basis outside of authorised clinical settings iv) Evaluation results can be communicated to the public (R10) to help facilitate public trust e) Ensure regular review (annually or as needed) of principles and practices for application of AI in healthcare settings f) Establish clear frameworks for liability and responsibility of AI when deployed in the healthcare system. This should: i) Distinguish by application/output	implemented across different settings as part of standard practice i) Support policy makers to stay abreast of international best practice (Food & Drug Administration (FDA), TGA or EU)	and responsibilities to be established by the TPA regulatory body

ii) Distinguish by level of supervision iii) Distinguish by level of associated risk iv) Establish clear criteria for insurance coverage		

R9: Understand the impact of funding models (research, adoption, and deployment) and the extent to which they enable development, adoption, and deployment of AI technologies within our healthcare system

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Complete a gap analysis of research and development capabilities within New Zealand. This could inform the development of funding models that require and/or reward developments for supporting positive healthcare outcomes in New Zealand (considered in conjunction with the outcomes of R3:a) b) Consider establishing a suitable funding model to facilitate the deployment of AI healthcare research	c) Measure the proportion of locally-produced AI developments that are deployed in domestic healthcare settings compared with those that are exclusively seeking international markets. This should: i) Be used to maintain an understanding of AI capabilities being developed locally ii) Inform research funding policies that incentivise or require benefit to be delivered to the New Zealand healthcare system	• R9:a could be carried out by various agencies or institutions including, but not limited to: ○ Manatū Hauora ○ Te Whatu Ora ○ Te Aka Whai Ora ○ MBIE ○ Universities • R9:a could be informed partly by R4 • R9:a should be considered in conjunction with outcomes from R3:a • R9:a-c might necessitate the establishment of a research and development leadership body for AI in healthcare • R9 could inform R20

Theme 4: Establishing confidence and trust

Establishing a sense of confidence and trust in AI technology is important. Effective engagement with the public, various tiers of the healthcare workforce and those in research and development will help to build confidence. Clear communication of AI limitations, risks and associated evaluation outcomes, coupled with the appropriate frameworks for governance, will support AI deployment and grow confidence and trust in AI-enabled technologies across the healthcare system.

R10: Develop an effective communication strategy

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Enable the delivery of relevant targeted information to stakeholders (public, healthcare workforce, research, and development workforce etc.) to build awareness of and confidence in AI technologies. This might include: i) Present and future potential for improved healthcare outcomes ii) Clear communication around benefits and limitations of AI iii) Associated risks of members of the public using AI as an alternative and/or replacement to consulting with a healthcare professional iv) Inevitability of errors (including types of errors, rate of errors, and comparison of error rates in settings where AI is not in use) v) National and international use cases b) Ensure that targeted information and training is available to AI in healthcare	d) Develop forums and operational teams to evaluate stakeholder confidence related to the use of AI in the healthcare system and consider necessary adjustments to any communications. This could be used to inform future communication strategies on a wider range of topics	• R10:a should be consistent with principles 12 and 14 • R10:c should engage with the relevant agencies to ensure activities are compliant with relevant regulations such as the TPA. Communication mechanisms could look like: ○ Public forums ○ Social media content ○ Accessible material in healthcare settings ○ Accessible material on healthcare websites • R10:d could be carried out by a relevant agency and/or independent research group

governance and decision-making bodies at all levels c) Ensure transparency around evaluation and implementation processes/frameworks to provide confidence in decision-making processes		

R11: Identify resourcing requirements to ensure that training and targeted information are developed and provided to the appropriate stakeholders

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Complete a scan of the healthcare workforce (and training pipeline) to determine relevant targeted information necessary for stakeholder groups (to compliment R10:a) b) Understand future resourcing and capability requirements and establish pathways to build relevant skill sets c) Monitor AI companies that indicate potential capability for AI technology to provide training of healthcare staff and/or health students d) Consult with training providers (including universities, accreditation bodies etc.) to develop evaluation mechanisms and criteria where adoption of AI tools for training of clinical staff and/or students would be acceptable and appropriate	f) Ensure continuing provision of training and support for the use of AI in healthcare g) Monitor evolving AI and healthcare landscapes to determine further areas for deployment of AI training capabilities	• R11:a should ensure resourcing pathways established are consistent with, and complimentary to, the Manatū Hauora Health Workforce Strategic Framework[i] and the Te Whatu Ora/Te Aka Whai Ora Health workforce plan 2023/24 • R11:d-f should be mindful of supervision requirements outlined in principle 10

[i] https://www.health.govt.nz/publication/health-workforce-strategic-framework

e) Develop an understanding of future AI training needs for health students and healthcare practitioners		

R12: Understand the wider implications of AI technology on healthcare delivery

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Carry out assessment of factors such as cultural and environmental impact b) Ensure access to technical resource for government agencies responsible for ensuring data privacy c) Determine appropriate frameworks for establishing dynamic informed consent	d) Evaluate mid-term impact on cultural and environmental factors	• R12:b might include agencies/official bodies such as: ○ Te Mana Mātāpono Matatapu | Office of the Privacy Commissioner ○ The Government Chief Privacy Officer

Theme 5: Tackling inequity

The adoption of AI in healthcare should not just replicate our current health outcomes. AI technology deployed in our healthcare settings should facilitate better outcomes for everyone in Aotearoa New Zealand. This necessitates developing an understanding of where our greatest health needs are and ensuring that we deploy technologies that help to close equity gaps.

R13: Ensure that the adoption and deployment of AI in healthcare settings improves health equity

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Include appropriate, New Zealand-specific, equity metrics in any evaluation of AI tools. These metrics might include: i) The tool's effectiveness across various population groups	e) Evaluate mid-term impact on health equity metrics	• R13: a(i) might be monitored by Te Whatu Ora and Te Aka Whai ora, and overseen by Manatū Hauora at a system-level • R13:b and c should be consistent with principle 7 • Ensure that AI tools support the provision of healthcare in a way that is no more biased

ii) The burden of disease the tool is designed to address across different population groups b) Require an equity impact and bias assessment before launching any AI tool in the public healthcare system c) Develop a framework for ongoing systematic evaluation of AI tools to understand the impact on health inequity (including annual reporting) and bias. This should: i) Be flexible to assess various types of AI ii) Inform decision-making bodies, funding bodies, research institutions and the technology development sector d) Develop frameworks and/or principles for AI development that highlight the need to address inequity and bias in healthcare delivery from the starting point of the development process		than human decision-makers (consistent with principle 15) • Quantitative metrics of inequity should be considered when establishing the appropriate communications strategy (R10). Effective communication of metrics could help to generate an informed public discussion • Ensure that evaluation outcomes from R13 are captured and communicated back to stakeholders through the appropriate channels. This should ensure ongoing transparency and work to maintain confidence and trust

Theme 6: Te ao Māori

Unique to the Aotearoa New Zealand context is Te Tiriti o Waitangi. Relevant iwi, hapū, whānau, and Māori organisations should be included in decision-making processes as partners alongside the Crown. Partnership should be evident throughout all stages of project life-cycles spanning conception, planning, governance, design, and implementation.

R14: Ensure adequate representation of Māori as Tiriti partners at various levels of the healthcare system

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Develop appropriate frameworks relevant to the deployment of AI in healthcare delivery in partnership with relevant iwi, hapū, whānau, and Māori organisations to give effect to Te Tiriti b) Develop a strategy to build Māori capacity including investment into workforce training, data access, data-sharing with appropriate Māori health providers, etc	c) Evaluate short-term healthcare outcomes against evaluation framework to determine the extent to which the principles of Te Tiriti have been upheld d) Evaluate Māori workforce capability against healthcare needs	• Oversight for this could be supported by various agencies and groups including: ○ Manatū Hauora ○ Te Whatu Ora ○ Te Aka Whai Ora ○ Relevant Māori authorities

R15: Establish the principles of Māori data sovereignty and their implications on the use of AI in healthcare settings

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Develop engagement between relevant ministries and relevant Māori authorities to ensure that the application of Māori data sovereignty principles with respect to AI in healthcare delivery is carried out appropriately b) Establish engagement forums that enable robust discussions around	e) Ensure the ongoing maintenance of Māori data sovereignty with respect to AI in healthcare delivery	• Effective partnership with Māori, whānau, hapū, iwi, and Māori organisations presents an opportunity for Aotearoa New Zealand to lead globally in addressing Indigenous AI health-related issues • R15:b should enable discussions amongst Māori leaders, and between Māori leaders and the appropriate government agencies

practical applications of the principles of Māori data sovereignty. Discussions might include: i) Empowering relevant iwi, hapū, whānau and Māori organisations to determine metrics of health, wellbeing and hauora for their own communities ii) Ensuring Māori control over Māori data and considerations of potential outcomes iii) Establishing appropriate tikanga for collecting, classifying, storing, accessing and using Māori data iv) Appropriate mechanisms of co-design as partners to Te Tiriti		

R16: Develop actions to build sufficient Māori capabilities across various workforces including data science, healthcare and governance

Short-term (1-2 years)	**Mid-term (2-5 years)**	**Considerations**
a) Understand the current representation of Māori in the data science, healthcare, and AI development industries b) Develop a strategy to build Māori workforce capacity including investment into workforce training, data access, data-sharing with appropriate Māori health providers, etc	c) Ensure continuation of strategy to build Māori workforce capacity including investment into workforce training, data access, data-sharing with appropriate Māori health providers, etc	• R16 could be supported by various agencies and institutions including but not limited to: ○ MBIE ○ Universities ○ Relevant Māori authorities

Theme 7: Data and systems

We cannot talk about AI without also talking about data and inference. Implementation of AI technologies within our healthcare system requires inference from large data sets. This highlights issues such as data definition, data collection, data storage, data privacy, data sovereignty and security as well as the safety, reliability, and effectiveness of the inference these data enable.

R17: Ensure processes are put in place to maximise quality of national data collection

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Identify areas of inadequate health data and ensure strategic priorities are set to address data shortages that would support the deployment of AI in healthcare delivery b) Identify computing requirements to enable on-shore data storage, model hosting, and technology development c) Expand the healthcare data strategy to consider factors relevant to data collection and data use for AI. This could include: i) The potential for individuals to opt in or opt out ii) The mechanisms for consent and the impact of individual consent on people groups (e.g., whānau, communities) d) Ensure robust data collection mechanisms and understand implications of AI tools being used for populations that are underrepresented in current data sets	f) Ongoing measurement of data quality and the appropriateness for AI applications	• New Zealand has some unique data sets and ability to link national data sets through the Integrated Data Infrastructure. This presents an opportunity for New Zealand with a competitive advantage for AI in healthcare delivery

e) Explore mechanisms for data linking across data sets outside healthcare, being mindful of data sovereignty		

R18: Establish transparent protocols for health data access for the development and implementation of AI within the healthcare system

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Establish protocols for data access and use for AI related development and implementation. This should: i) Consider principles of Māori data sovereignty (see R15) ii) Include guidelines for testing of AI tools using national data sets		• R18 could be supported by relevant agencies and bodies including but not limited to: ○ Manatū Hauora ○ Te Whatu Ora • R18 could be supported through engagement with the soon to be established TPA regulator

Theme 8: Exploring future opportunities

AI introduces various opportunities to improve outcomes in our healthcare system. Creating environments that foster research and innovation can enable us to take advantage of new and exciting opportunities.

R19: Resource AI in healthcare research needs

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Support for research should span all relevant areas such as data science and health professional training	b) Monitor and evaluate outstanding healthcare needs and the extent to which current resourcing is sufficient to achieve future aspirations for AI in healthcare delivery	• R19 should support needs outlined in R1, R4 and R5

R20: Develop a Centre of Research Excellence for AI research with a specific focus on healthcare delivery

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Determine resourcing and responsibility for Centre of Research Excellence b) Establish international research and development capabilities and develop strategic relationships c) Specific research strategy should be defined based on (1) need within the healthcare system, (2) capacity and capability within domestic research capabilities (or in existing research partnerships), (3) likely impact of research outcomes (4) likely time to deployment and (5) ease of deployment/implementation	d) Monitor success and support continuing research	• Centre of Research Excellence should be developed in partnership with the health system to ensure guardianship of health data that can be used for research and development, and to ensure research addresses relevant health system needs • R20:c could be informed by MBIE's Te Ara Paerangi | Future Pathways initiatives • R20 could be supported by agencies like Te Amorangi Mātauranga Matua| Tertiary Education Commission

R21: Understand enablers and barriers to AI development, commercialisation, and deployment

Short-term (1-2 years)	Mid-term (2-5 years)	Considerations
a) Understand from existing AI companies the factors within the research and development space that served as enablers for development, adoption, and deployment of their AI technologies b) Understand from existing AI companies the various enabling technologies that facilitate enhanced AI development	e) Continue to support deployment of novel AI technologies	• Mechanisms for connecting with AI companies might be supported by groups such as the AI Forum of New Zealand

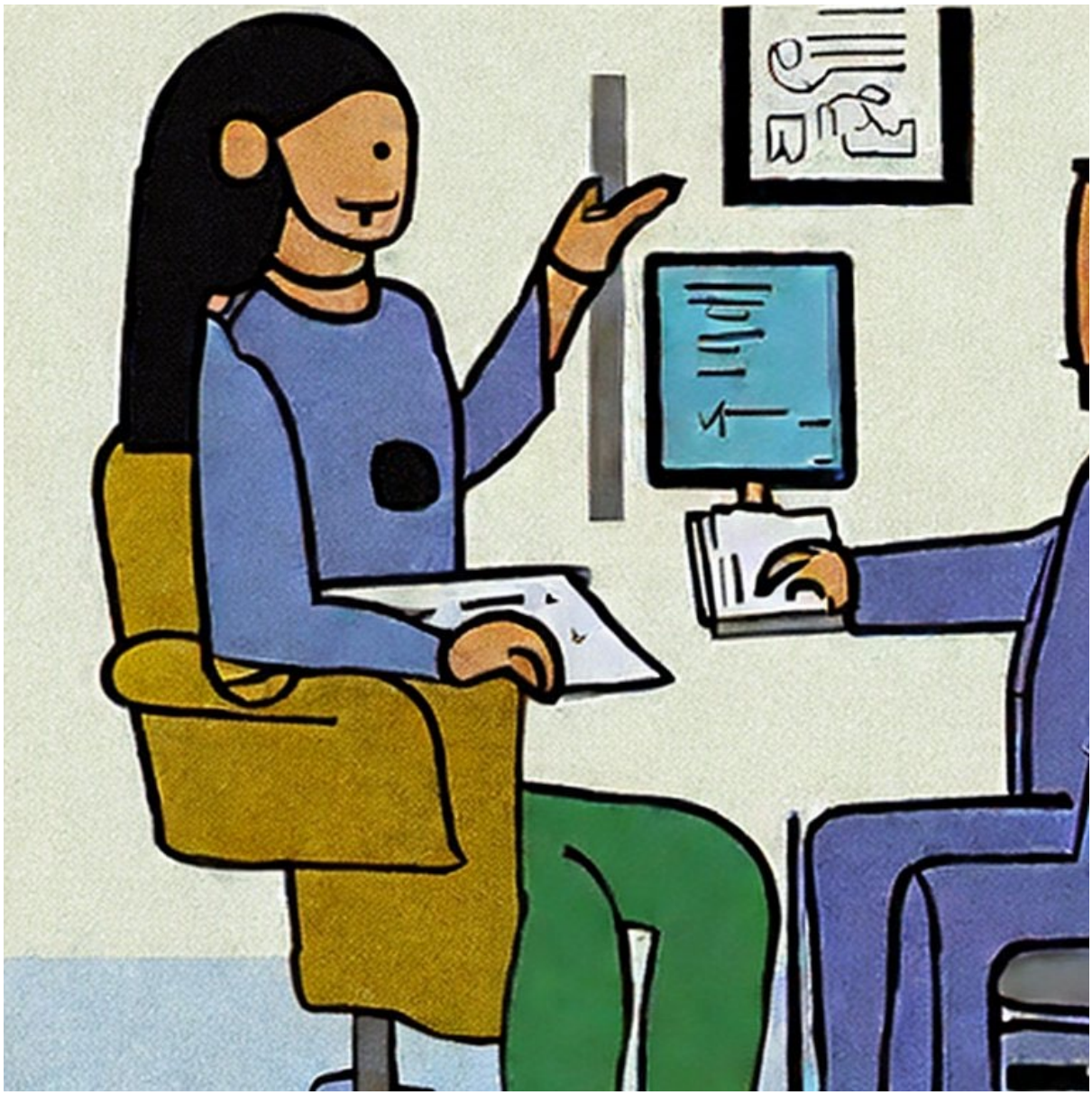
c) Generate targeted information that provides advice to start-up companies attempting to deploy AI healthcare technology in New Zealand d) Generate advice for AI companies to navigate the legislative environment e) Generate advice for AI companies to navigate commercialisation processes		

R22: Establish a range of networks to allow stakeholders to discuss relevant issues relating to AI in health care delivery

Short-term (1-2 years)	**Mid-term (2-5 years)**	**Considerations**
a) Establish forums that: i) Span various stakeholder groups (e.g., occupation, iwi, ethnicity, locality, research, industry, government etc) ii) Highlight factors that are at the forefront of the public conversation, immediate concerns to be addressed and clear opportunities to capitalise on b) Establish annual expo (or something similar). An expo should: i) Allow those from the research and development sector to showcase current and future potential ii) Be used to inform the healthcare profession of available emerging AI technologies iii) Enhance public visibility of emerging technologies	e) Maintain and support continued development of relevant networks	• R22 could be supported by various agencies and institutions including, but not limited to: ○ MBIE ○ Manatū Hauora ○ Te Whatu Ora ○ Te Aka Whai Ora ○ Universities ○ Te Apārangi | Royal Society of New Zealand ○ Relevant Māori authorities

c) Establish support roles and/or networks for AI businesses. Support should: i) Provide advice to businesses about deployment of technology in the New Zealand healthcare environment ii) Provide mechanisms to support SMEs with regulatory costs d) Establish links with key players in the global AI ecosystem e.g., Microsoft, Amazon, etc		

4. BACKGROUND



Prompt: A drawing of a robot taking medical notes while listening to a patient in a hospital. Created using Stable Diffusion on huggingface.co

Key messages

- Implemented well, there are ways in which AI can be deployed into the healthcare system within the next few years. Key actors such as Manatū Hauroa | Ministry of Health and Te Whatu Ora | Health New Zealand are already undertaking the task of digitising patient records which will support the ongoing rollout of AI technologies
- AI introduces many potential benefits coupled with new and challenging risks to manage. Various countries have started to build or amend regulations to manage AI deployment in healthcare settings
- There are AI governance frameworks emerging at national, international, and supranational levels. Decision makers might consider reflecting on these emergent frameworks to inform the most suitable governance structures for supporting safe and effective decision-making around AI in our national healthcare services
- Various ethical challenges will need to be addressed by policy makers and administrators

4.1. AI

There is no universally agreed definition of AI, but there are categories of AI that are starting to proliferate and will be referred to in this report. [9] AI is a space where rapid advances have rendered some common definitions outdated – for example, the Organization for Economic Cooperation and Development (OECD) describes "machine-based systems [that make] predictions, recommendations, or decisions", [10] which does not capture the recent advent of generative AI. Nevertheless, it is useful to have a working definition that will be able to incorporate novel developments in the next few years. For this report, we use AI to mean technologies that simulate human intelligence: the ability to learn, reason, self-correct, and create new content.[i]

> For this report, we use AI to mean technologies that simulate human intelligence: the ability to learn, reason, self-correct, and create new content.

In some parts of this report, our analysis applies to AI generally, while in others, we refer to a specific type of AI or a category of AI. One distinction that will be relevant is between what we are calling predictive AI and generative AI, as described in section 1. This distinction is important when we evaluate the performance of these AI tools. For predictive AI, standard evaluation protocols exist, and can be used – comparisons can easily be made between, say, error rates for these tools vs existing best practice. For generative AI, on the other hand, best practice for evaluation has not been established, although advances are being made. [2]

We have chosen to err on the side of inclusivity in our definition of AI. Some comparatively simple algorithms feature in our case studies, such as the COVID triage tool described in case study 1. Despite its relative technical simplicity, this case study is widely understood and demonstrates the potential benefits to consumers of harnessing data as well as having similar implications for clinician

[i] Importantly, although we are talking about the ability to mimic or augment human intelligence, there will be tasks where AI outperforms humans.

adoption, privacy, Māori data sovereignty, and health equity as many of the more sophisticated tools.

Finally, we do not address artificial general intelligence (AGI) in this report. The definition of AGI, like AI, is debated – Sam Altman of OpenAI defines AGI as AI that is better than humans, [11] while other definitions include AI that has common sense or consciousness, or can understand context without human intervention, or whose ability to do cognitive tasks is not limited by its training. [12,13] Estimates about when AGI is likely to arrive vary from two years to two decades. This is due to variation in definitions chosen and confidence in the technology. This does not alter our view of the current and near future opportunities for AI within the New Zealand health system, nor our recommendations for how to realise these opportunities. Within a longer time frame, however, AGI may offer opportunities we cannot currently envision, as well as posing additional considerations for its safe adoption.

For predictive AI, standard evaluation protocols exist, and can be used – comparisons can easily be made between, say, error rates for these tools vs existing best practice. For generative AI, on the other hand, best practice for evaluation has not been established.

Case study 1: Northern Region COVID triage tool

The Institute for Improvement and Innovations, as a part of the former Waitematā District Health Board (DHB), used medical and administrative data held by three Auckland DHBs to identify 13 variables for inclusion in a logistic regression model designed to predict a patient's risk of hospitalisation or death, providing an output as a numeric value in the range 0-100%. Risk values were categorised as low (0-9%), medium (10-19%), or high (20% or higher). [14] The tool was developed using data collected during the Delta outbreak and was prepared in time for the Omicron outbreak.

The aim was to support the COVID-19 care in community hubs and primary care providers to receive timely information to prioritise clinical care to people most at risk of adverse outcomes. Such an approach was essential in the peak of the Omicron outbreak to use available resources effectively. The algorithm did not replace but aimed to support clinical judgement, which became the primary driver of ongoing treatment and follow up.

Because the tool was built using data that included hospital visits, people who have difficulty accessing health services would have been underrepresented in the data and thus may not have been well served by the model. The implementation of the COVID triage tool by the hubs took account of this by prioritising the following people within the implementation model: Māori and Pacific peoples; people living in high deprivation; people living with disability; and those not enrolled with a primary care provider.

Importantly, the tool was embedded in the dashboard that was used by community teams, alongside explanations and caveats, enabling easy access to the tool and the ability to make an informed choice as to how and when to use it. The score became especially helpful when teams were faced with triaging thousands of cases a day. However, the response from primary care

clinicians was mixed, with some users preferring to prioritise based on their judgements rather than trusting the algorithm.

Although AI was not used in this case study, the development, implementation, and use of the COVID triage tool provide valuable learnings about how algorithms can utilise routinely collected individualised electronic health information to support medical decision-making.

4.2. AI for Aotearoa New Zealand's health system

Over recent years the digitisation of systems at the former DHBs and within Te Whatu Ora has increased,[i] necessitating strong governance which provides a solid foundation to ensure that AI tools are implemented safely. [15] A National AI and Algorithm Expert Advisory Group (NAIAEAG) has been established consisting of both internal and external members. The advisory group is responsible for reviewing proposals to develop or put into practice any new models of AI in our national health services. [15] Various voices are represented within the advisory group including experts in AI, ethics, clinical, research, Māori health, data, digital, privacy, legal, and innovation. Proposals are considered against an assessment framework that considers various themes and perspectives (see Annex 2 for the full assessment criteria).

A national AI and algorithm expert advisory group (NAIAEAG) has been established.

To date various AI initiatives, from concept to research to implementation, have been reviewed and advice has been provided. There are also several areas of development that remain a work in progress within Te Whatu Ora which include:

- The ongoing digitisation of our health system
- Development of a national data platform
- National data governance and data access protocols
- The adoption of the previously developed Te Pokapū Hātepe o Aotearoa |New Zealand Algorithm Hub
- Development of a post-implementation review checklist to assess outcomes of newly implemented AI technology

The recently released *Long Term Insights Briefing* (LTIB) confirms that Manatū Hauora expects increased adoption of AI and machine learning in the next ten years to lead to improvements in all stages of health care (see Annex 3).[16] The LTIB focuses on the impact of precision health in Aotearoa New Zealand and assesses the associated risks and benefits. Four key areas are identified as being critical in terms of implementation of precision health technologies. These include:

- Embedding Te Tiriti o Waitangi (Te Tiriti)
- Empowering individuals, whānau, and communities

[i] Throughout the engagement process we heard mixed feedback about the extent to which our national health records are digitised. Our understanding is that different DHBs utilised different record keeping systems creating difficulties when merging the various systems.

- Achieving health equity
- Efficiency and financial sustainability

Subsequent to the release of the LTIB, Manatū Hauora has been developing a programme of work in conjunction with Te Whatu Ora and Te Aka Whai Ora| Māori Health Authority to explore next steps for the implementation of precision health initiatives. We hope this report supports the ongoing work within these agencies.

Internationally, there is an increase in national strategies, [17,18]legislation, [19] and strategic investments[20] that signal use of AI, in recognition of the potential value it can provide including within healthcare settings. However, amongst stakeholders we consulted, there was a strong sentiment expressed that AI should not be implemented in our healthcare sector unless it is clear that outcomes for Māori will improve as a result. Deployment strategies should consider mechanisms for ongoing monitoring and reporting to ensure that AI technology is indeed supporting the aspirations of our New Zealand healthcare system, including providing better outcomes for those who experience historically worse outcomes. Deployment and implementation steps are discussed further in section 7.

4.2.1 Therapeutics Products Act (TPA)

New Zealand's *Therapeutics Product Act 2023* (TPA) comes into force in September 2026 and will impact the implementation of AI in healthcare. A regulatory body for the act is being established and it is expected that the policies and evaluation mechanisms introduced by this actor will be crucial for ensuring that key stakeholders understand the use of AI within clinical settings. Local developers that we engaged described watching the progress of the recently passed TPA closely, anticipating that it would impact on their product deployment.

Where AI is to be used for a therapeutic purpose, it will be designated Software as a Medical Device (SaMD) under the act. Some examples of potential SaMDs include cell phone based diagnostic software, robotic surgery machines, and diagnostic imaging software. Making SaMD available for use in New Zealand will constitute a supply and may require market authorisation, licence, or permit from the regulatory body. Clinical trials of software for safety and performance will also likely to be impacted.

A regulatory body for the act is being established and it is expected that the policies and evaluation mechanisms introduced by this actor will be crucial for ensuring that key stakeholders understand the use of AI within clinical settings.

Decisions around the types of AI-based SaMDs approved for deployment in New Zealand will be shaped by our contextual needs and healthcare aspirations. While regulatory mechanisms are still being established, international settings may provide some guidance for us. We discuss regulation in more detail in section 4.3.2. Alongside the TPA, our team has preliminarily assessed how existing legislation might impact on the use of AI in healthcare (see Annex 4). A more in depth analysis will be necessary moving forward.

4.3. Governance of AI for healthcare[i]

There are many stakeholders with an interest in AI for healthcare including government agencies, researchers, industry bodies, and consumers. Effective governance should consider the at times competing interests of various stakeholder groups and work to facilitate the development of appropriate policy frameworks, regulatory settings, and system design. Adopting a co-ordinated national approach that is internationally connected could support the smooth deployment of AI into our healthcare system (spanning clinical and non-clinical uses), enabling us to realise the many benefits on offer. There are various elements of governance to consider for the deployment of AI in our health system. These include, but are not limited to, global governance of AI, regulatory considerations, and data governance (including data privacy, data access, and data sovereignty). [21-23]

4.3.1. Global governance

Establishing clear frameworks for the governance of AI in healthcare is a work in progress across jurisdictions, with the development of new AI technology significantly outpacing the generation of appropriate governance frameworks. [24] Maintaining oversight of international governance trends will enable local decision makers to reflect upon the impact of our national governance on system design, regulation, and international relationships. This presents an opportunity to adopt or adjust relevant governance mechanisms where the outcomes would improve the delivery of healthcare in New Zealand.

As nations work toward establishing mechanisms of governance suited to their context, consideration should be given to our place in the international landscape. Some AI companies boast more users or subscribers than the total population of entire nations (likely including our own), highlighting the potential for commercial entities to exert some influence over the control of AI globally. [25] It is therefore prudent to consider supranational organisations that support the development of global governance frameworks. Guidance from the WHO suggests that international oversight may be a necessary measure to mitigate the risk that some bad players may ignore ethical and human rights obligations in pursuit of economic gains. [21]

Examples of global initiatives for the governance of AI more generally have already emerged such as the Global Partnership on Artificial Intelligence (GPAI) launched in 2020 that brings together leaders from research, industry, government, and society. [26] At present, GPAI boasts 29 member nations including New Zealand. Member nations are brought together by their collective commitment to the values outlined in the OECD recommendations on AI. [27] Activities are intended to support the development of responsible AI practices globally, grounded in the shared principles of human rights, inclusion, diversity, innovation, and economic growth. [26]

Examples of global initiatives for the governance of AI more generally have already emerged such as the Global Partnership on Artificial Intelligence (GPAI) launched in 2020 that brings together leaders from research, industry, government, and society.

[i] We consider in this section AI that will be formally adopted within the health sector. Consumer facing tools that are not under the control of the health sector will be more challenging to bring into any governance arrangement or regulations.

4.3.2. Regulatory considerations

Appropriate regulation of AI technology is proving to be a challenge globally. While not specific to healthcare, our office has produced an overview of regulatory settings internationally to highlight the challenges of regulatory design and areas of emerging international consensus.[i] Consensus principles are still forming and the legislative and regulatory pathways to enact these principles vary across jurisdictions.

Regulation of healthcare specific AI will require ongoing development and will need to address research, development, and clinical settings. New AI tools are being developed rapidly and with them, a growing urgency to implement appropriate regulatory settings. [28,29] Various bodies have stated their preference that a risk-based approach be adopted for the regulation of AI including supranational organisations such as the EU,[28] and commercial entities such as IBM. [30,31] A risk-based approach would involve regulating AI technology according to risk category and specific to use-cases, rather than regulating the technology itself. This could be operationalised by establishing different rules for different risk tiers, creating clearly defined risk categories, and defining what acceptable and unacceptable levels of risk look like within our national healthcare context. Our engagements echoed this sentiment with some stakeholders stressing the need for a dynamic regulatory environment moving forward.

In future, regulatory mechanisms should allow for mature AI technologies with accepted evaluation frameworks to be deployed into healthcare settings, while ensuring sufficient guardrails to prevent the deployment of less mature AI technologies ahead of full audits of their performance.

Regulatory mechanisms should allow for mature AI technologies with accepted evaluation frameworks to be deployed into healthcare settings, while ensuring sufficient guardrails to prevent the deployment of less mature AI technologies ahead of full audits of their performance.

As with the application of any tool within the medical field, appropriate safeguards to ensure patient and practitioner safety are essential. Table 1 describes how some international jurisdictions are approaching regulating AI in healthcare at the time of writing this report.[ii]

[i] https://www.pmcsa.ac.nz/topics/artificial-intelligence-2/

[ii] To date there is no such thing as 'medical grade' generative AI. The development of appropriate evaluation and regulatory mechanisms will be a key milestone in deploying such technologies within our national healthcare settings. This is a matter of ongoing discussion and will require input from various sectors. In the interim some of our national agencies, including Te Whatu Ora, have released guidance advising against the use of LLM's citing lack of evaluation for known potential risks (including privacy breaches, inaccurate information, inequities and bias, lack of transparency, data sovereignty, and intellectual property) and unintended consequences.

Table 1: An overview of how some international jurisdictions are introducing new, or potential regulations for AI in healthcare

Jurisdiction	Relevant regulation
Australia	Australia has set out a National AI strategy and established system-wide principles for deploying AI across sectors. [32] Work specific to healthcare is still under development however, the Australian Medical Association, [33] Royal Australian College of General Practitioners, [34] and the Digital Health Cooperative Research Centre[35] have all vocalised a preference for a risk-based approach to AI regulation. [36] At a federal level, the Therapeutic Goods Administration (TGA) provides some guidance on the use of SaMD that builds on the Australian Register of Therapeutic Goods. [37] At a state level, individual states are managing the use of software like ChatGPT within their hospitals. [38]
Canada	Some uses of AI as SaMD are currently regulated by Health Canada under the *Food and Drugs Act*. [39] Health Canada has issued guidance outlining software classification criteria. The Digital Health Review Division within the Therapeutic Products Directorate's Medical Devices Bureau is responsible for reviewing AI technologies to support the issuance of licences related to digital health technologies (including AI). [40] Operating across jurisdictions, Health Canada jointly published *Guiding Principles: Good Machine Learning Practice for Medical Device Development* alongside the US Food and Drug Administration (FDA) and the UK's Medicines and Healthcare products Regulatory Agency. [41] The report outlines ten guiding principles intended to promote the deployment of safe, effective, and high-quality AI medical devices.
Europe	AI-based SaMD and some types of AI diagnostic tools are currently regulated in the EU through 2017/745 Medical Devices Regulations (MDR) and the 2017/746 In Vitro Diagnostic Medical Devices Regulation (IVDR). [42] These mechanisms allow for pre-market control, clinical investigation requirements, surveillance across the device's lifecycle, and enables EUDAMED - a database of medical devices available to use in the EU. [43] The proposed EU AI Act has different requirements depending on a particular tool's level of risk. Risk categories are self-assessed, however, any AI used in medical devices is considered high risk and requirements of the proposed Act have been harmonised with the medical devices regulations described above. [30]
Singapore	The Singapore Health Sciences Authority (HSA) are responsible for regulating health products. In April 2022, the HSA issued relevant to software that falls under the definition of a medical device as stipulated in the Health Products Act. [44] The guidelines recommend that software medical device manufacturers adopt a total product life cycle approach to managing medical device software. This could include oversight of requirement management, risk assessment, software verification/validation, change management and

Jurisdiction	Relevant regulation
	traceability through the duration of the software's life cycle. The HSA also give attention to post-market surveillance acknowledging that new risks may emerge when the software is deployed into a real-world context (see case study 3).[45]
UK	The National Health Service AI Lab has funded the establishment of the AI and Digital Regulations Service, a multi-agency collaboration between four organisations including: • The National Institute for Health and Care Excellence • The Medicines and Healthcare products Regulatory Agency • The Health Research Authority • The Care Quality Commission This service maps out the regulatory and evaluations pathways for AI-enabled technologies.[46] The Medicines and Healthcare products Regulatory Agency coordinates post market surveillance of products and has developed synthetic data sets to support the validation process.[47]
US	The US FDA has three pre-market pathways: 510k clearance, De Novo classification, or pre-market approval for medical devices, and this includes some health-based AI technologies.[48] The FDA has approved a list of medical devices that utilise AI and indicate products that have been reviewed and authorised for market.[49] A specific action plan was developed in 2021 by the FDA for managing SaMD.[50] More recently, in response to the growth in AI medical applications, the FDA has acknowledged that current regulatory pathways cannot manage all subsets of AI and has plans to develop a more flexible regulatory environment.[51]

The definitions outlined in section 1 describe both predictive and generative AI, an important distinction to consider when developing regulation. At present, the use of predictive AI models is familiar in both public and private sectors. Standard evaluation practices can be used for predictive AI tools such as comparison of error rates between the tool and current best practice. Conversely, generative AI models are not fully understood at this point in time and present new risks such as hallucinations. *The AI Revolution in Medicine: GPT-4 and Beyond* described one such example where GPT-4 hallucinates while generating medical notes.[2] After launching a separate session to cross-check the original outputs, GPT-4 was able to produce a robust critique of the original generated medical notes. This demonstrates a useful cross-checking mechanism but also highlights the risks of generative AI tools being inappropriately used in clinical settings. Such risks are what regulations will need to mitigate.

Throughout the report writing process stakeholders we engaged described various trade-offs that will need to be navigated to arrive at the optimal regulatory settings. We explore some of these trade-offs in brief.

Safety versus innovation

Regulation should prioritise patient safety yet be permissive enough to allow access to the many advantages that AI technologies have to offer healthcare. While designing adequate regulations presents a challenge, there are examples to look to for guidance (Table 1).[52]

We heard throughout the engagement process that the development and deployment of innovative technology requires some risk appetite and tolerance. With the rapidly evolving technology landscape, it is unlikely that regulation will keep pace with the rate of development. While there are risks posed by AI, these should not be seen as reason to block its use entirely. This need for risk tolerance can sit in contrast to the risk-averse nature of healthcare delivery and regulatory settings have potential to discourage or limit innovation. Failure to innovate also involves risk, especially if the innovation in question has the potential to enhance the availability and effectiveness of healthcare. Governing bodies will need to balance regulatory settings to maintain patient safety while also ensuring that the health system benefits from continued growth and innovation. [21,53,54]

> The development and deployment of innovative technology requires some risk appetite and tolerance.

Transparency and explainability

With the increased availability of black box type AI that limits the ability to interrogate how outputs are generated, there are accompanying concerns around AI transparency and explainability. [21] Arguably, while transparency and explainability are important factors, they are attributes that we demand more urgently from AI technologies than from human decision makers.[4] However, this enhanced vigilance for AI systems may be a useful way of highlighting the importance of explanations in healthcare more generally.

Policy makers must also consider factors such as liability and accountability where the use of AI tools is implemented in healthcare settings. Who should be held to account if the advice generated by an AI tool is incorrect? Conversely, what should be the outcome if AI generated advice is correct but ultimately ignored by healthcare staff? [21,23]

4.3.3. Data governance

'Big data' and accompanying data governance challenges are not new. However, the rapid emergence of increasingly sophisticated AI tools and their dependence on large datasets places emphasis on the need for strong data governance frameworks. Implemented well, effective data governance can ensure that available data are fit for purpose, leading to enhanced trust in the governance frameworks, governance bodies, and in the data itself. [55] We discuss fit-for-purpose data further in section 6.4.

The growth of digital health data and increasing computational capabilities generate significant opportunity for the use of AI in healthcare delivery. Access to large datasets is a requirement for the

training, validation, and testing phases of AI product development.[56] However, the use of such data for these tasks generates concern. Decision-making bodies are faced with the challenge of safeguarding privacy and autonomy for the individual, and communities, while supporting access to the potential benefits of data collection and use in AI technologies.[21]

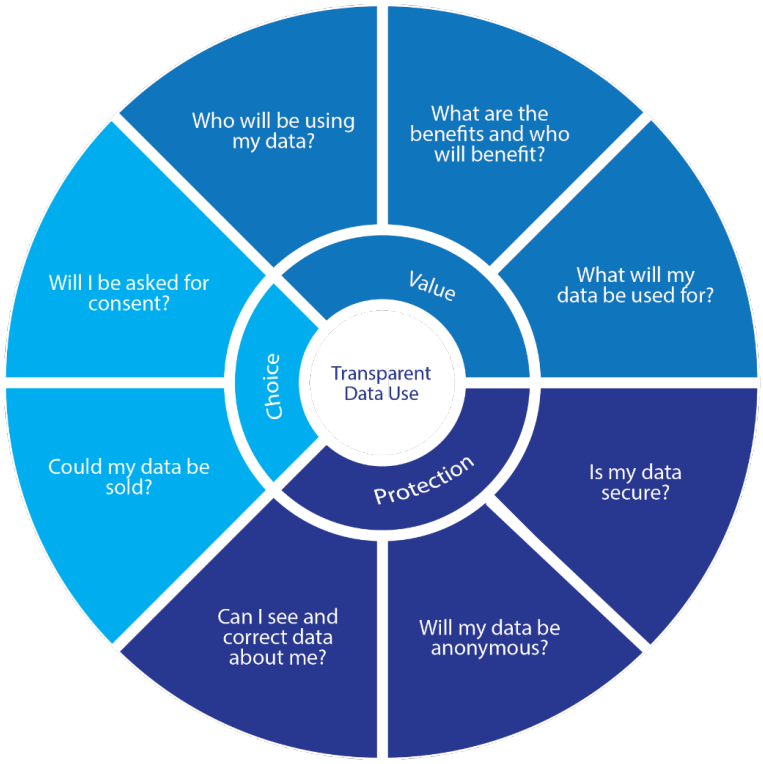


Figure 1: What matters to people about their data use (reproduced from Data Futures Partnership, 2021)[57]

Data governance arrangements should be informed, at least in part, by social licence. The former Data Futures Partnership (now New Zealand Data Trust) released a report in 2017 that builds on a series of engagements with stakeholders across the motu to provide some insight into what matters to people about their data use[57] and later produced guidelines for data users,[58] including a tool to guide discussions with individuals about whether and how to share their data (see figure 1). While ongoing engagement will be necessary to remain abreast of what matters to individuals and communities, these eight questions provide useful starting points for governing bodies to consider.

Data governance mechanisms vary across jurisdictions, however one OECD study identified that across member states, co-ordinated public policy frameworks were lacking. *The Recommendation on Health Data Governance* was adopted by the OECD Council in 2016[59] and set out 12 principles that health data governance frameworks should provide for, as follows:

- Engagement and participation of stakeholders in the development of a national health data governance framework
- Co-ordination within government and co-operation among organisations processing personal health data to encourage common data-related policies and standards
- Reviews of the capacity of public sector health data systems to serve and protect public interests

- Clear provision of information to individuals about the processing of their personal health data including notification of any significant data breach or misuse
- The processing of personal health data by informed consent and appropriate alternatives
- The implementation of review and approval procedures to process personal health data for research and other health-related public interest purposes
- Transparency through public information about the purposes for processing of personal health data and approval criteria
- Maximising the development and use of technology for data processing and data protection
- Mechanisms to monitor and evaluate the impact of the national health data governance framework, including health data availability, policies and practices to manage privacy, protection of personal health data and digital security risks
- Training and skills development of personal health data processors
- Implementation of controls and safeguards within organisations processing personal health data including technological, physical and organisational measures designed to protect privacy and digital security
- Requiring that organisations processing personal health data demonstrate that they meet the expectations set out in the national health data governance framework

In addition to the rapid emergence of AI tools, global events such as the COVID-19 pandemic demonstrated the value in utilising large volumes of health and health-related data (case study 1). Following the Health Data Governance Summit in June of 2021 the WHO released a summit statement describing how the increased pressure for health data that emerged from COVID-19 highlighted long standing data governance issues. [60] The WHO called on member states to work toward a common data governance framework and practices, underpinned by a set of unifying principles.

4.3.4. Local governance

Locally, [61] our data collection is governed by data protection and privacy legislation: Privacy Act 2020, Health Information Privacy Code 2020, and Health Information Governance Guidelines. [i] Governance bodies are responsible for interpreting and applying rules, decision-making, and supporting the resolution of any conflicts that arise related to data use. [62] As repositories of health data grow, suitably developed data governance frameworks to capture the available benefits, while mitigating related risks are necessary.

As repositories of health data grow, suitably developed data governance frameworks to capture the available benefits, while mitigating related risks are necessary.

[i] Other relevant legislation includes New Zealand Public Health and Disability Act 2000, Health Act 1956, Health (Retention of Health Information) Regulations 1996, Cancer Registry Act 1993 and Cancer Registry Regulations 1994, Official Information Act 1982, and Public Records Act 2005.

We should consider the appropriateness of adopting and adapting governance frameworks and/or guidance from elsewhere to our national context, recognising that simple modifications to existing frameworks may not be sufficient. [63] Within the Aotearoa New Zealand context, there should be consideration given to our obligations under Te Tiriti o Waitangi (Te Tiriti), respecting te ao Māori views, and tikanga Māori. Te Tiriti is a founding document of government in New Zealand and its principles will require consideration on an ongoing basis as the breadth of applications for AI in healthcare delivery continues to evolve. Section 6.1.1 describes our obligations under Te Tiriti in greater detail. While we have yet to arrive at an agreed governance framework for AI in Aotearoa, in health or otherwise, there are early examples to look to (see figure 2).[63]

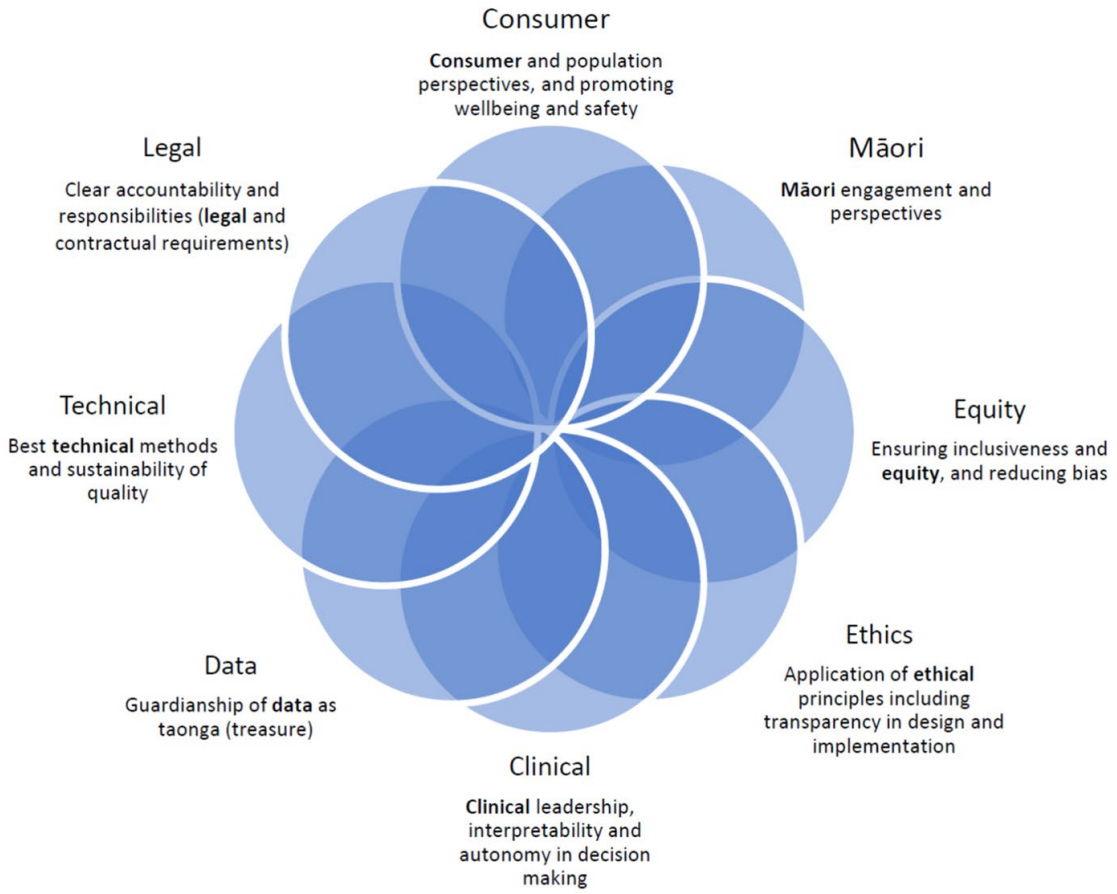


Figure 2: AI governance checklist: eight domains for consideration (from Whittaker et al., 2023) [63]

There are existing agencies and entities whose areas of work will intersect with governance of AI in our healthcare system. Governance bodies will be required to stay abreast of ongoing conversations that extend beyond the healthcare sector itself. While not exhaustive, we list some of the relevant players here.

The work of Government Chief Data Steward will almost certainly impact on the adoption of AI for healthcare delivery. [64] Their responsibilities include:

- Setting the strategic direction for government's data management
- Leading the state sectors response to new and emergent data issues
- Co-developing a Data Stewardship Framework
- Leading the Government's commitment to accelerating the release of open data

The breadth of work of the Chief Data Steward necessitates working in cooperation with other government system leaders within the digital space, including the Chief Digital Officer, [65] Chief Information Security Officer, and Chief Privacy Officer.[53] Consideration should also be given to the Mana Ōrite relationship agreement that was established with the Data Iwi Leaders Group in 2021.

Another entity whose work programme will likely address matters relevant to the governance of AI in healthcare is Te Mana Mātāpono Matatapu | Office of the Privacy Commissioner (OPC). [66] Tasked with providing independent advice to government, the OPC serves many functions, outlined in the *Privacy Act 2020.* [67] In September 2023, the OPC issued advice around the use of AI tools, building on an initial set of expectations released in May 2023.

Throughout the engagement process we heard how access to well-curated, diverse data is key to improving outcomes, and that AI-enabled software offers major opportunities. Local AI developers described their experience of accessing local data as complex, something that they worried could slow the rate at which we are able to achieve improved health outcomes locally. The establishment and communication of effective governance frameworks might provide some clarity in this area.

Recently, Whittaker et al. published a checklist of governance questions as a framework that the authors recommend be considered throughout the AI lifecycle. [63] We point to the checklist, reproduced in table 2 as a useful starting point for governance bodies.

Table 2: Table reproduced from Whittaker et al., 2023[63]

AI Lifecycle	Concept development	Access to data for pre-processing, labelling or model development	Validation or implementation of an existing AI model
Appropriateness	• Is the problem they are trying to solve understood? • Is that problem associated with a large quantity of data which an AI model could learn from? • Would analysis of that data be on a scale so large and repetitive that humans struggle to carry it out effectively?	• Is the problem they are trying to solve understood and could the AI offer advantages over what is currently provided? • Is that problem associated with a large quantity of data which an AI model could learn from? • Would analysis of that data be on a scale so large and repetitive that humans struggle to carry it out effectively?	• Is the problem in our context understood and does the AI offer benefits over the current situation? • Has it been sufficiently tested for accuracy against empirical evidence? • Has it been used in practice elsewhere and does it perform as expected? • Has it been, or how will it be, sufficiently validated with data from the Aotearoa New Zealand population? • How will its impact be evaluated?

AI Lifecycle	Concept development	Access to data for pre-processing, labelling or model development	Validation or implementation of an existing AI model
Consumers/ population perspectives	• Would the community support the use of data/AI for this problem? • What difference would it make to the community/population? • Are there any risks to wellbeing and safety? Who bears the risk (is it the same people who are likely to benefit from the project)? Can they potentially be mitigated?	• Would the community support the use of data for this problem? • What difference would this AI make to the community/population? • Are there any risks to wellbeing and safety? Who bears the risk (is it the same people who are likely to benefit from the project)? How will they be mitigated? • Has the project engaged with people/groups who may be impacted by the use of this AI?	• Would the community support the use of data/AI for this problem? • What benefits does it bring to the community? • Has the project engaged with people/groups who may be impacted by the use of this AI? • Would we need to communicate with our patients/ population about this use of AI? • Are there any risks to wellbeing and safety? Who bears the risk (is it the same people who are likely to benefit from the project)? How will these be avoided or mitigated? • Do our patients need to have this use of AI communicated with them?

AI Lifecycle	Concept development	Access to data for pre-processing, labelling or model development	Validation or implementation of an existing AI model
Māori perspectives	• Are those involved able to design this AI in a culturally appropriate manner? • Does the project adhere to the relevant Te Mana Raraunga principles and Te Ara Tika principles (acceptability and accountability to Māori, relational ethic to working with Māori, equitable benefits through focus on mana, equity and distributive justice)? • Does the project embed a te ao Māori perspective through a te Tiriti based partnership approach?	• Are those involved able to develop this AI in a culturally appropriate manner? • Has the team engaged with Māori or had any Māori governance input/oversight? • Are there any potential issues from a te ao Māori perspective?	• Was the AI developed in a culturally appropriate manner? • Has the development and validation had any Māori governance oversight or input from Māori? Have any concerns been raised and addressed?
Equity and Fairness	• Are there likely to be any bias or discrimination issues with addressing this problem using the available data?	• Are there likely to be any bias or discrimination issues with addressing this problem using the available data? • Have any fairness issues been identified to date and are there measures to mitigate risks arising from potential bias?	• Has it been evaluated for bias across ethnic groups, genders, other? • Can it be used fairly? • Have any fairness issues been identified to date and are there measures to mitigate risks arising from potential bias?

AI Lifecycle	Concept development	Access to data for pre-processing, labelling or model development	Validation or implementation of an existing AI model
Ethical principles	• Is the data able to be used ethically and safely and in the spirit within which was collected? • Does the project comply with the NEAC standards? • Does the project intend to embed the ethical principles, such as transparency and human autonomy? Does the team agree to transparency of their methods and model?	• Is the data able to be used ethically and safely and in the spirit within which was collected? • Does the project comply with the NEAC standards? • Does the project intend to embed the ethical principles, such as transparency and human autonomy? • Is there intended to be human oversight of the AI and how will that occur? • Does the project intend to comply with our principle of transparency?	• Can the AI be used ethically? Are the ethical principles embedded in its development and use? • Have they disclosed the AI for transparency? • Will a human still be involved in oversight/final decisions? • Does the project comply with the NEAC standards?
Clinical perspectives	• Could the outputs of a model be tested for accuracy against empirical evidence? • Would model outputs lead to problem solving in the real-world from a clinical perspective?	• Can the outputs of such a model be tested for accuracy against empirical evidence? • Will model outputs lead to problem solving in the real-world from a clinical perspective?	• Can the AI be implemented in our clinical workflow and operational context? • Will it be accepted and explainable/understood by clinicians? • Is there clinical and service support in our DHB? • Has there been an assessment of feasibility/readiness, communication and training? • Who is responsible for ongoing audit and monitoring from a clinical perspective?

AI Lifecycle	Concept development	Access to data for pre-processing, labelling or model development	Validation or implementation of an existing AI model
Data availability, quality, appropriateness, and completeness	• Is the necessary data available? • Is the data of sufficient quality and completeness? • Is there any further consent required for this use of the data?	• Is the problem associated with a large quantity of data in our DHB which an AI model could learn from? • Is the necessary data available in the manner needed to run the AI? • Is the data of sufficient quality and completeness? • Is any further consent required for the use of the data? • If data is provided, is there a plan for storage, destruction or retention? • Are there any risks around privacy, confidentiality, security or reidentification?	• Is it clear what data the model was developed with and then tested on? • What data has/will it be validated with? Is that data of sufficient quality and completeness? • Is it an appropriate use of the data according to how the data was collected in our DHB? • Are there risks around data privacy, confidentiality, security, or re-identification? • Will data and/or results from the model come into our data warehouse?
Technical processes	• Are those involved able to design according to the DHBs technical specifications?	• Are those involved able to develop and test according to the DHBs technical specifications? • Is the data and process safeguarded with appropriate security and confidentiality? • Does the team agree to transparency of their processes, data, methods and models?	• Have they disclosed the AI so that it can be evaluated technically – model chosen and methodologies, feature engineering, parameter tuning? • Does it comply with our technical specifications? • Who is responsible for ongoing audit and monitoring from a technical perspective?

AI Lifecycle	Concept development	Access to data for pre-processing, labelling or model development	Validation or implementation of an existing AI model
Contractual and Legal issues	• Can we agree on a co-design contract with respect to DHB principles, confidentiality, accountability, and shared IP? • Have the necessary approvals been given (Research & Learning, HDEC etc)?	• Can we agree on a contract with respect to our principles, privacy/confidentiality, security, Māori data sovereignty, IP, accountability, publication and commercialisation plans? • Have the necessary approvals been given (Research & Learning, HDEC etc)?	• Can we agree on a contract with respect to DHB principles, use of data and outputs, privacy/ confidentiality, Māori data sovereignty, ongoing monitoring and audit, regular review processes? • Is accountability/ liability between parties clear and understood? • What will happen should the AI fail?

4.3.5. Māori data sovereignty

Because AI is built on data, any consideration of its use in Aotearoa New Zealand will need to engage with the issue of data sovereignty and Māori data sovereignty in particular. We discuss this in greater detail in section 6.1.

4.4. Ethical Issues relevant to AI in healthcare

A number of ethical issues apply to AI technologies in any context. These have important consequences in healthcare. We have summarised some well documented risks of AI in table 3.

Table 3: Ethical risks of AI generally

Bias and discrimination	AI tools replicate biases in the data on which they are trained and/or the socio-economic structures that generated these data. For example, Amazon designed a tool to assist in hiring decisions that prioritised men over women[59] and facial recognition routinely has variable performance by ethnicity.[60]
Impingement on data privacy	AI can make use of novel sources of data in ways that most people are not in a position to understand, consent to, or opt out of. For example, during our engagements, one person described the potential to use the angle at which a person is holding their phone as an input determining in real-time the targeted ads or other content the individual will be exposed to.

Lack of transparency and accountability	Automating decisions that affect people's lives makes it more difficult to understand and challenge a decision, potentially preventing people from exercising their civic and human rights. In the Netherlands[61] and Australia,[62] algorithms designed to detect tax and benefit fraud wrongly identified large numbers of people, with serious consequences.

Biomedical ethics, along with a Māori framework of ethics called Te Ara Tika, form the basis of decisions made by Kāhui Matatika o te Motu | National Ethics AdvisoryCommittee[68] who advise Manatū Hauora on ethical matters in research and service provision. Incorporating AI into healthcare may require policy makers and administrators to apply these ethical lenses to their decision-making when considering the adoption of AI tools. Guidance specific to the potential ethical challenges of adopting AI in health systems has been released by the WHO.[21] Here we highlight some issues this guidance raises to give the reader a sense of the decisions with which policy makers and administrators will be faced.

As automated decision-making is incorporated into clinical practice, new ethical challenges will emerge. One of these is that AI tools can operate as a black box, meaning that end users – both clinicians and patients – and sometimes even developers cannot understand how a decision, prediction or output arose. WHO guidance includes a principle that AI should be transparent and explainable, while acknowledging that optimising AI tools for these factors means not optimising for accuracy.[21] Automated decision-making also raises questions about when it is appropriate for AI tools to be used without human supervision, and when human supervision is essential. We provide some suggestions on this question in principle 10.

As automated decision-making is incorporated into clinical practice, new ethical challenges will emerge.

AI adds ethical complexity to health promotion, which strives to "make the healthy choice the easy choice".[69] Health promotion has often involved attempts to increase health literacy and/or to change public policy. As a concrete example, health promotion campaigns in the area of smoking cessation have targeted making people aware of the health harms of tobacco (an approach that seeks to increase health literacy) while also advocating for smokefree environments (an approach that targets policy). The fields of psychology and behavioural economics have contributed to health promotion via the 'nudge', where the environment and circumstances in which people make decisions can be manipulated to influence the decision.[70] Nudges in themselves are ethically controversial due to questions about a lack of transparency and undermining of autonomy.[71] In the context of AI, predictive AI tools' powerful targeting ability combined with the ease with which generative AI can produce bespoke messaging could lead to particularly effective nudges. Despite the potential benefits of this use of AI to both individuals and the health system, the sophistication of the targeting and bespoke messaging may heighten concerns that using AI to nudge constrains people's autonomy around their health behaviours.[21]

Another ethical challenge is in using AI predictions in allocation and prioritisation. In section 6.4 we point to mechanisms by which such processes could be equity promoting. However, in some

circumstances there is the potential for the use of AI predictions in allocation or prioritisation decisions to compound structural inequity. One example would be incorporating a prediction of compliance with post-operative immunosuppressant regimes into the allocation of organ transplant and other health behaviours more generally. [72] The ability for AI to determine organ transplant allocation based on behavioural predictions may be viewed as discriminatory.

Finally, AI's ability to produce detailed insights about individual health and health risks raises ethical questions about who should have access to these insights. As genetic testing has advanced societies have already grappled with questions of whether children or siblings of people who have specific genes have a right to know[73,74] and these discussions will only intensify as understanding of omics expands. Likewise, individuals have the right not to know about their likely future health states. [21] Providers of healthcare, including public health systems and health insurance, may be better able to plan with good information about likely health needs over the long term, but this raises the possibility of genetic discrimination in financing health systems. [75] Similarly, risk factors related to lifestyle could be better understood with advances in AI, especially from wearable devices or shopping patterns. To date as a society New Zealand has decided that healthcare should be publicly funded with no distinction based on lifestyle but the perpetual debate between personal and social responsibility for health is likely to be reignited with richer lifestyle data available.

AI's ability to produce detailed insights about individual health and health risks raises ethical questions about who should have access to these insights.

Automation bias

As AI introduces increasing automation to our health system, it will be necessary to take measures to mitigate automation bias. This occurs when people defer to the judgement of an automated system even when it is incorrect, often becoming less vigilant about critically appraising the information or decisions of the automated system. [76,77] Generative AI tools create a real danger of automation bias, both in medical practice, and in medical education: both medical professionals and medical students might fall 'out of the loop', through over-reliance on AI tools that are 'good enough most of the time'. In the airline industry, where autopilot is in charge of planes for large segments of any given flight, automation bias is well understood, and mature strategies for its prevention have been developed. [78] Pilots ongoing certification and professional development includes deliberate strategies to prevent entrenching automation bias. The health system might consider taking a similar approach.

To date as a society New Zealand has decided that healthcare should be publicly funded with no distinction based on lifestyle but the perpetual debate between personal and social responsibility for health is likely to be reignited with richer lifestyle data available.

4.4.1.Consent, transparency, and disclosures

Questions around consent arise for two issues related to the use of AI in the health system. The first is in the use of patient data to build or test AI tools. Data collected by health providers in the process of delivering care are important for informing public health and health service activities. This is permitted by the existing *Health Information Privacy Code 2020*.[79] However, the use of data for building AI tools raises new questions, especially where data could be shared outside of the health system. The potential for de-identified data to be re-identified because of the power of AI presents some risk and may need to be factored into future consenting processes. Additionally, as increasing numbers of developers will seek access to data, a general approach to facilitate administering consent will be needed. Two possible models are:

- Dynamic consent: a platform that would facilitate the consent process and allow for preferences to be changed or request for data re-use[80]
- Meta-consent: a retrospective and prospective model of consent with the option of general consent or refusal without dealing with large volumes of consent requests[81]

Finally, there will be factors unique to our national context. Honouring Māori data sovereignty may require new ways of thinking about data use. For example, we heard throughout the engagement process that some consider de-identified data to still have a whakapapa, necessitating appropriate tikanga for collection, handling, and storage.

The second issue to raise questions of consent is in using AI tools to provide patient care. Informed consent for any medical treatment is required by the *Code of Health and Disability Services Consumers' Rights 1996*. Informed consent is an interactive process that builds trust between the patient and the doctor.[82] The introduction of AI to our healthcare settings introduces some complexity to this process. For example, will patients need to consent for every application of AI, such as patient triage in an ED, or for clinical note taking? Where AI becomes a standard part of clinical care, could refusal to consent to the use of AI become challenging to accommodate? What are the implications for the patient if the use of AI demonstrates a superior standard of care (as is the case in medical imaging).[83,84] Further, where an AI system has a black box nature, to what extent can a patient grant valid informed consent?[85] Important conversations are required at various system levels around issues such as consent processes and disclosure requirements.[83]

Governing bodies should take care when implementing consent processes to avoid scenarios where patients risk not being treated unless they sign away their information, or are overwhelmed by terms and conditions, and privacy policies.[86] It might be valuable to explore meaningful consent strategies such as meta-consent and dynamic consent to understand their appropriateness, feasibility, costs, and what type of digital infrastructure would be necessary to support them.

5. ADDRESSING HEALTHCARE NEEDS USING AI

Prompt: Small wearable AI to help monitor vital health signs. Created using Stable Diffusion on midjourneyai.ai

Key messages

- The health system in Aotearoa New Zealand is under considerable strain. AI offers potential benefits that, if deployed well, could alleviate strain at various tiers of the healthcare system
- Determining the economic implications of AI technologies is complex and traditional cost-saving measures do not capture the full impact. A 'return on investment' assessment to articulate the costs and benefits of AI acquisition and deployment, capturing value in both financial and health terms, might prove more appropriate than a narrow approach that focuses purely on cost-savings
- There are a multitude of potential applications of AI technology in our healthcare sector. This report identifies automation of administrative tasks, capitalising on available data, AI-enabled sensing technology, computer vision, and generative AI as some applications that are either already available or that are likely to be in the near future
- Beyond clinical settings AI has the potential to enhance our health research capabilities. Examples include production of rapid literature reviews, employing generative AI tools to communicate research outputs tailored to specific audiences, enhanced design and execution of experiments, generation of hypotheses for testing, and the ability to collect, integrate, analyse, and interpret large bodies of data
- Regular horizon scans to capture new advances and opportunities will enable decision makers to deploy AI technologies that are most suitable to address our contextual needs

5.1. Potential benefits of AI

Our health system, like others around the world, is under strain. We face increasing demand for health care from a population that is ageing and experiencing an increase in chronic diseases like diabetes. Patients face long waits to receive some treatments. Concurrently, healthcare staff in New Zealand report low levels of job satisfaction, with a 2019 study reporting one in three nurses planned to leave their roles within a year.[87] In a 2022 survey of doctors, 93% reported that there was 'definitely' a workforce crisis[88] and in July 2023 there were roughly 8,000 vacancies in the national health system.[89] The COVID-19 pandemic undoubtedly exacerbated these strains in the health system. While these pressures are not new, the current economic climate is not favourable for significant increases in the health budget. Against this backdrop, the potential of AI to address some of these stresses is exciting.

In table 4 we identify where AI tools are likely to be available in the short, medium, and long term and which areas of the health system they are likely to benefit. This table is not exhaustive, and certain technologies may affect multiple parts of the health system or have an uncertain time horizon. It does, however, highlight that 1) the potential benefits are systemwide rather than concentrated in particular areas and 2) there are near term opportunities in addition to a longer term pipeline.

Table 4: Benefits of AI in healthcare (Table adapted from Bajwa et al., 2021 and Gunatilleke, 2022). [90,91]

	Role of AI	Short Term (0-2 years)	Medium Term (2-5 years)	Long term (5 years +)
Administrative	Plan		• Optimise supply chain and logistics	
	Manage	• Automate high-volume repetitive tasks • Harmonise health records across different administrative units • Support more efficient administrative auditing	• Assist in prioritising resources when hospitals are overwhelmed • Harmonise health data collation • Integrate patient records and automate certain tasks to free up clinician time	• Seamless delivery of healthcare information between patients and healthcare providers
	Deliver	• Patient messaging and communication in multiple languages		• Support efficient auditing of records and AI platforms
Enhancing care delivery and improving health equity	Plan	• Optimise patient and staff scheduling	• Design new patient care pathways • Improve patient safety across various harm domains[92] • Manage patient flow in a hospital • Identify likely demand for care	• Predictive and anticipatory care • Reliable access to medical information to patients of all levels of health literacy
	Manage	• Memory jogging for healthcare professionals and patients • Triage in emergency departments or outpatient referrals	• Generate insights from unstructured data like reports and notes • Reduce workload and demand on healthcare professionals	• Connect unstructured data between healthcare settings

	Role of AI	Short Term (0-2 years)	Medium Term (2-5 years)	Long term (5 years +)
	Deliver	• Enhance investigations and diagnosis of disease • Mental health support • Support image interpretation • Telehealth services • Virtual assistants • Individualise treatment planning and management • Support care delivery and automating processes (case study 7)	• Differential diagnoses via LLM[2] • Personalise patient communications in a patient's language (Annex 6) • [93]Local AI tools developed for local problems • Patient-led biometric monitoring through wearable devices for real time monitoring (case study 4) • Personalise healthcare • Access personal health information/get reassurance or referral • Prevent avoidable errors and adverse drug effects with AI intervention • Enhance human-led procedures (surgeries)	• AI companions for people with disabilities, illnesses like dementia, and for elderly people[94] • Generate information in various languages • AI assisted selfcare, health monitoring, personalised care • Virtual hospitals • Remote palliative care
Population health and health policy	Plan	• Better use of scarce services and skilled workers • Predictive analytics • Identify high-risk groups		• Ascertain Indigenous ownership rights to data • Prioritise health budgets
	Manage	• Public health surveillance	• Identify emerging health threats	
	Deliver	• Targeting of screening programmes • Targeted health promotion campaigns • Disease prevention	• Use digital humans to encourage healthy behaviours (case study 9)	

	Role of AI	Short Term (0-2 years)	Medium Term (2-5 years)	Long term (5 years +)
Research and enterprise	Plan	• Assist with project planning	• Assist with clinical trial enrolment	• Identify important knowledge gaps
	Manage	• Support clinical trials by patient selection and tracking adverse events[95]	• Collect, store, and manage data	
	Deliver	• Academic and research literature mining • Educational support for healthcare staff in training [96,97] • Utilise digital twins (case study 4) • AI drug discovery and drug leads • AI tools can be marketed internationally	• Mitigate culturally unsafe research practices • Analyse data • Produce stakeholder-appropriate outputs of research findings • Summarise prior research	

5.1.1. Return on investment

In our publicly funded health system, the economic implications of a given therapy or technology are as important as its clinical value. Many headline figures declare the potential of enormous cost savings from the use of AI in healthcare: US$150 billion in the year 2026,[93] US$200b-US$360b or 5-10% of US health spending annually within the next five years[98,99] and US$17,881 and US$289,643.83 per day per hospital for diagnosis and treatment respectively in ten years. [100] Despite these headline numbers, it is not clear that the studies underpinning these estimates have sufficient internal and external validity to guide potential cost-savings to the New Zealand health system. Indeed, it is difficult to imagine a convincing estimate of a single system-wide cost-saving derived from what is likely to be – at least initially – ad-hoc adoption of individual technologies.

Even at the level of individual AI tools, economic evaluations are rare: one systematic review found 20 eligible studies over a five year period, compared with over 120,000 describing a new AI tool in a single year. [101] Another systematic review identified 66 potentially eligible studies, of which only six provided sufficient information to incorporate into the analysis. [102]

Apart from the lack of costings, a more fundamental problem with attempting to quantify cost-savings from the incorporation of AI into the public healthcare system is that this framing does not fully capture the economic implications of interest. In a blog post about valuing public health, relevant for our discussion, the Chief Economist at Public Health England noted "…the aim of public policy is not solely to achieve maximum savings to public sector budgets, but also to improve

people's health and wellbeing and reduce health inequalities." [103] This also means that the financial savings of a healthier population over the longer term are omitted. A common feature of studies included in systematic reviews is that the economic analyses tend not to account for indirect costs – and sometimes even direct costs – of acquiring and using a new tool, nor for its overall health impact. [101,102] Finally, tools which detect disease that would otherwise have gone undetected will lead to increased demand for treatment, meaning that even if the cost per test is reduced, this does not necessarily imply a systemwide cost saving.

With few robust evaluations of the economic impacts of AI adoption, and evaluations undertaken in other contexts not necessarily predicting likely outcomes in New Zealand, a more useful framing of the potential economic value of adopting AI tools in the healthcare sector is return on investment (ROI). An ROI framing brings the upfront costs to the forefront (the 'investment') while capturing value in both financial and health terms. Importantly, although ROI is typically expressed as $X realised per $Y invested, a portion of the $X returns is an assigned value of changing health status and not actual monetary value that will be realised in healthcare budgets. [104,105] Choosing an ROI lens over a narrower cost-saving lens is more in line with the wellbeing framing of government finances that New Zealand adopted in 2019.

With few robust evaluations of the economic impacts of AI adoption, and evaluations undertaken in other contexts not necessarily predicting likely outcomes in New Zealand, a more useful framing of the potential economic value of adopting AI tools in the healthcare sector is return on investment (ROI).

We highlight in table 5 the domains which might be considered by policy makers and administrators in predicting likely ROI.

Table 5: Likely components of ROI calculations

Investment	• *Direct costs.* Costs related to purchasing, licensing, or developing a tool • *Indirect costs.* For example, staff training, software updates, infrastructure maintenance, transition costs
Returns	• *Cost savings.* Augmenting of clinical and administrative staff to reduce human time needed for a given function (see examples in section 5.2.1), more efficient operation of health facilities (see examples in sections 5.2.1 and 5.2.2) • *Changing demand.* Novel technologies (c.f. replacing existing tests and treatments) and technologies that are more accessible will create new demand. More accurate diagnostic tests could increase treatment demand by detecting more cases, or reduce treatment demand by reducing overdetection, or change demand in complex ways by, for example, increasing demand for treatments common in early stages of disease pathways while simultaneously decreasing demand for those common later • *Improvements in health status of individuals and the population.* Tools that improve diagnosis and treatment (sections 5.2.1, 5.2.2 and 5.2.3) and public health (section 5.2.2) will result in improved health, which can be captured as QALYs or DALYs and easily converted to a monetary value[106] • *Improvements in health equity.* AI has the potential to improve health equity by improving the health of groups who tend to be in poorer health (section 6.5). This will result in net improvements in the health status of the population which can again be captured by QALYs or DALYs

Case study 2: Volpara Health

Volpara Health is a Te Whanganui-a-Tara | Wellington-based software company. The company has been listed on the ASX since 2016, and its success comes from its AI image analysis capabilities applied in a pragmatic and robust manner on mammograms (breast X-rays). Today, Volpara's software is employed in over 40% of US breast cancer screenings (over 15-million women a year) along with BreastScreen South Australia, Queensland and Victoria, and a handful of private clinics in New Zealand. The company has recently been named the global Microsoft Life Sciences Partner of the Year. [107]

One measurement that the software returns is breast density, the proportion of fibrous and glandular tissue in the breast as compared to fatty tissue. Breast density is an independent breast cancer risk factor and can significantly reduce the ability of a radiologist to see a breast cancer in a mammogram. [108] Ralph Highnam, Founder of Volpara Health describes how "the original discussions about the importance of breast density started in the mid-1970s, but the subjectivity of judging it by eye led the field to fall into disrepute until AI driven measurements emerged." Volpara is a world-leader in automated measurement of breast density from mammograms through the application of both traditional AI (based on X-ray physics and techniques from computer vision) and modern AI with deep learning to improve the algorithmic robustness. In New Zealand, early work on Volpara's products[109] indicate that differences in breast density might explain some of the health disparities that are seen in breast cancer.

An example of the Volpara scorecard for a patient is captured in figure 3. The scorecard reports that 24.4% of the patient's breast is fibrous & glandular tissue ('dense') rather than fatty[110]. The breast density has been entered into the Tyrer-Cuzick breast cancer risk model along with factors such as BMI and her lifetime risk of developing breast cancer has been worked out at 23% which might qualify her for genetic testing and/or additional screening using breast MRI. The scorecard indicates that for this patient cancers will be very hard to see with X-rays if they should develop. In the USA, such women might be offered additional screening using ultrasound.

Today, the European Society of Breast Imaging[105], and the FDA[111,112] in the US both recommend women are told their breast density when they are screened. Since receiving FDA clearance in 2010, Volpara has extended its range of automated, quantitative measurements to include radiation dose, breast compression and image quality and more recently breast cancer risk assessment has been included, where breast density has become a critical input. New Zealand, with its population size, focus on health disparities and frequency of breast cancer diagnosis, has the potential to be a global leader as a fast adopter for AI in healthcare that is clear, explainable, measurable, and impactful.

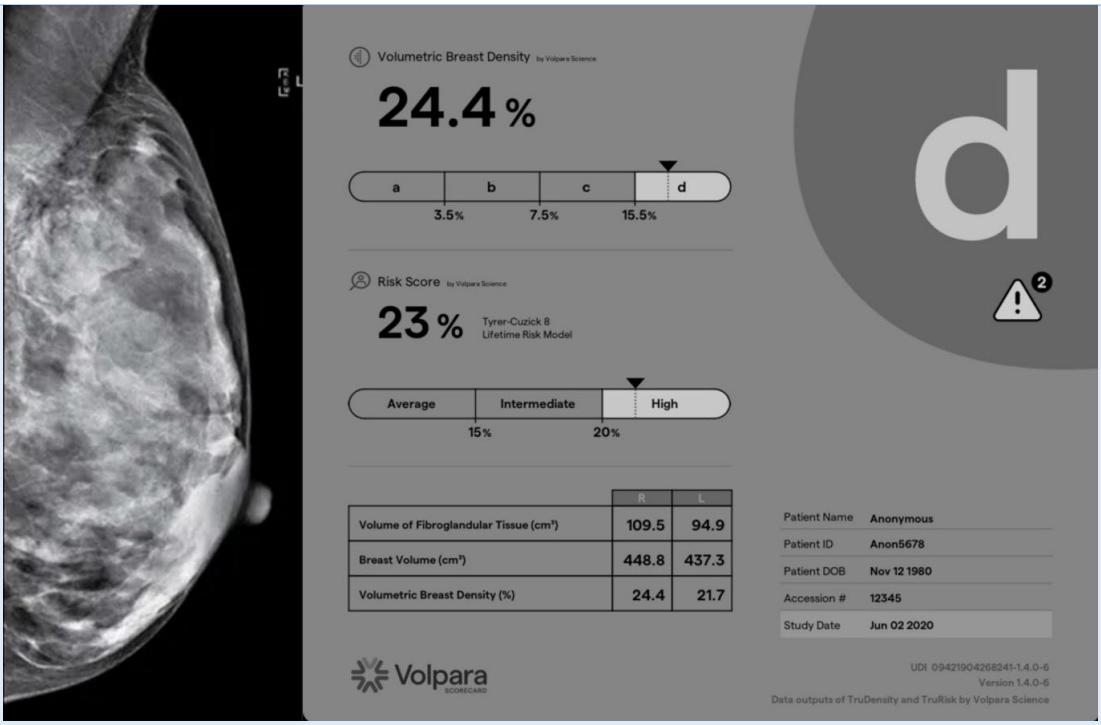


Figure 3: Example scorecard courtesy of Volpara Health

5.2. Current and near-future opportunities offered by AI

At the time of writing, there are abundant applications of AI technology to healthcare. Many of these are tools purpose-built to undertake specific tasks, while others take general purpose tools, like ChatGPT, and use them in a healthcare setting. We include examples of both uses here to demonstrate what is possible, while noting that the latter use is likely to be riskier because the tools are not 'medical grade'. Our examples focus on tools that are already available or are likely to be so in the near future, but we also offer a glimpse of what may be possible in the longer term. For example, case study 3 describes Singapore's use of AI in its public healthcare system. Not all features of Singapore's use of AI will be appropriate for our New Zealand context (see section 7.2), but it is an innovative example of what is possible at the system-level.

5.2.1. Automating administrative tasks

Within the health system, a significant amount of human resource – both clinical and non-clinical – is spent on administrative tasks. Some tasks are not complex but are time consuming. For example, clinicians must record their interactions with patients and sign off prescription requests, while sending patients reminders is useful for avoiding missed appointments and thus wasted resources. In the near future, AI medical assistants could record, process, and create notes through voice data during a consultation.[8,113,114] Some tools could also streamline communication and co-ordination in time-sensitive clinical scenarios (case study 7 and case study 5). Platforms to do these tasks already exist,[108] although use of such tools at this point in time risks contravening guidance from the OPC.[8]

AI could enhance clinical operations and scheduling. Every patient appointment requires scheduling, at minimum for a space and one clinician, but often for multiple clinicians and specialised equipment with uncertainty about the time required. Pharmacies and hospitals need to manage supply chains

for medicines and other consumables which each have their own patterns of demand. In the Singapore National University Hospital system, a dashboard for the ED shows clinicians and administrators descriptive information (for example, current capacity), predictive information (for example, the number of likely incoming cases) and prescriptive information (for example, instructions to decant patients to other hospital departments).[115] Closer to home, in our engagement we spoke to a data scientist who had been part of a team that built a model to predict ED presentations over three hour periods[116]. In order to benefit from using data in this way, our health system will need to find a way to utilise its resources – including human resources – dynamically.

Case study 3: Singapore, national AI strategy, and healthcare

Singapore released a National AI strategy in 2019.[17] The strategy identified that building an AI ecosystem required enablers such as:

- A partnership between research, industry, and government
- AI talent and education
- Data architecture
- Progressive and trusted environment
- International collaboration

Prior to the AI strategy, Singapore pursued digitisation and then the use of AI in its health system. In 2008, the Integrated Health Information System was founded by the Ministry of Health to lead the development of health technology projects and has since been rebranded as Synapxe. Synapxe's role includes supporting the Ministry of Health to enable technological innovation, providing technology to the public healthcare sector, enabling a digitally connected health ecosystem, and developing and bringing to market products aligned with Ministry of Health objectives.[117]

Principles for the country's use of AI in the health system were formalised in 2021 in its *Artificial Intelligence in Healthcare Guidelines*.[118] The guidelines are based on principles that have considerable overlap with the principles we introduce in section 2 and make recommendations for the development of AI around designing, building, and testing products and for the implementation of AI around the use, monitoring, and review of AI products. Singapore is cognizant of the risks of deploying AI in its health system and takes a proactive approach to mitigate these.

The development and rollout of AI tools in the Singaporean healthcare sector sits in the context of a broader initiative seeking to be a 'digital-first' society.[119] Several digital health initiatives have been developed, including some innovative AI tools:

SELENA

Singapore Eye LEsioN Analyser (SELENA+) uses yearly retinal scans from 100,000 patients as part of a screening program to detect major conditions like diabetic eye disease, glaucoma, age related macular degeneration, and cardiovascular disease.

Assistive Technology and Robotics and Healthcare

This initiative has the aim of people being independent and is being rolled out with older citizens and people with disabilities. Robots are being used to monitor mobility, help with personal care, and dispatch medicine and equipment.

Project Pensieve

With a declining birth rate and an ageing population, 80,000 seniors are forecast to be affected by dementia by 2030.[120] Individuals can sign up themselves or encourage a family member for an AI-based dementia test to enable early intervention and support, which is predicted to lead to better outcomes.

Our health system will need to find a way to utilise its resources – including human resources – dynamically.

5.2.2.Capitalising on data

AI, broadly conceived, opens up the ability to make use of a vast amount of data, from that routinely collected in clinical settings to data recorded by wearable devices (case study 4), and even data not directly related to health (for example sources such as an individual's purchasing habits or internet browsing). This presents both risks and opportunities.

One potential application is early identification of problems, either at individual or collective levels. At the individual level, wearable devices could provide early warnings of changes in health status. Collectively, signals such as alcohol sales, traffic volumes, or air quality could signal future public health issues in communities.

Case study 4: Project Otto

Project Otto is a biodata project run by Taylored Technologies utilising AI and systems biology to create a personalised health plan for users. Based in New Zealand, it is a five-year initiative dedicated to building a digital twin as a dynamic reference engine for optimal health and longevity.

The digital twin evolves by assimilating real-time data from the users wearable devices and diverse clinical diagnostics, and includes genetic data to generate a health profile of its user. This user health profile, compared with an 'optimised' digital twin, produces a tailored simulation with the goal of charting multiple pathways to improved health. Behavioural science tools such as precision nudging, alongside coached interventions ensure these pathways are actionable, guiding individuals towards their peak health.

Abundant accessible data about an individual also enables personalised medicine. For example, the optimal dose of post-transplant immunosuppressants differs both between people, and within the same person at different points in time as they respond to transplant or have additional medical procedures.[121] By using data to optimise dosage, the efficacy of medicines can be increased while costs can be reduced if drug use decreases.[122]

Finally, making use of data allows better targeting of resources and interventions. In Denmark, researchers used a rich data set from all Danish women to build a model to identify risk factors for breast cancer. Evaluation found that compared to standard screening where eligibility was determined solely by age, screening according to predicted risk could detect more invasive cancers for the same number of screens or detect the same number of cancers with fewer screens. [123]

Case Study 5: AI for ambulance dispatching

New Zealand's emergency medical service is facing pressure to handle increasingly high demand (for example, the impact of annual demand growth, COVID-19, an aging population, etc). Faster response times directly correlate with decreased mortality. For example, in 2019 the US Federal Government estimated that reducing their average national ambulance response times by one minute could save over 10,000 lives per year. [124] Machine learning can improve the responsiveness of emergency medical dispatch, a critical but challenging problem for emergency medical services. This problem comprises a variety of complex and interdependent offline (for example, managing paramedic shifts) and online decisions (for example, assigning staff to ambulances and assigning ambulances to emergencies) under a highly dynamic and uncertain environment. Additionally, we must balance various conflicting objectives, such as response times and staff workload.

The complexity of this combinatorial optimisation problem requires that we specifically design machine learning techniques to learn dispatch policies that perform well in any given unseen scenario. Associate Professor Yi Mei, a world leader in combinatorial optimisation from the Centre for Data Science and Artificial Intelligence, Te Herenga Waka |Victoria University of Wellington, has recently won an MBIE Smart Idea (Endeavour Fund) Grant to lead a project on machine learning for emergency medical dispatch, which extends the existing research of his PhD student, Jordan MacLachlan. Alongside Professor Mengjie Zhang, Dr Fangfang Zhang, and Kirita-Rose Escott, their prior work has demonstrated machine learning's superiority over a suite of expert-designed dispatch rules that approximate human dispatch behaviour, reducing simulated response times by up to 75%.[125,126] This research is in partnership with Wellington Free Ambulance, with the goal of developing a technology directly applicable to the real world.

Compared to standard screening for which eligibility was determined solely by age, screening according to predicted risk could detect more invasive cancers for the same number of screens or detect the same number of cancers with fewer screens.

Privacy enhancing technologies

The need to store, access, and process large amounts of medical data in a centralised location poses its own challenges and privacy concerns. [127] One of the challenges is the risk of compromising data from a single point of failure. [128] Instead of needing to accumulate data in one location, Federated Learning (FL) is a way of keeping sensitive patient data locally and only sending insights back to a centralised server as a way of training a larger model that can then update local models. The possible benefits include better data privacy, scalability of using AI, and avoiding network

congestion.[127] FL could be a way to share data for AI development while maintaining control of data in way that is consistent with Māori data sovereignty principles (see section 6.1.6) and complying with regulations around privacy.[129] Research into FL is still at an early stage, but this technology could provide an option to keep patient data within a clinical setting while also allowing for the development of better centralised models that might otherwise be compromised by limited data or computational power.[127] FL architecture shows potential for personalisation regarding in-home care[130] services and mobile or wearable devices (mHealth).[131] A wider set of 'privacy-enhancing technologies' are also being researched and developed, to help make data available for analysis and training while maintaining the privacy of individual records.

Case study 6: HomeCare

Evan Huang is a Year 12 student who created an AI robotics system called HomeCare for his school science fair. Evan was inspired to try to alleviate some of the lifestyle challenges experienced by his grandparents in their older age with health issues like dementia. He is also aware of the impacts of loneliness on older people and hopes his HomeCare innovation might help to address this in some small way.

HomeCare was created to be a home service robot that can assist a range of different stakeholders who may require assistance at home. The prototype robot pictured in figure 4 was built by Evan and uses a computer, VEX Robotics kits, and DIY parts. The conceptual design has functions in the head, body, arm, and the base of the mannequin depicted which, when developed, will allow for movement and for user interaction.

Evan hopes that the HealthCare module will connect users with telemedicine support and collect daily health data like blood pressure and temperature. It could also carry out prompting functions such as reminding users to incorporate exercise into their day or to take their medications.

Evan is a great example of the talent that exists in our younger generation. He is developing his ideas with the hopes of improving the lives of other people. Creating spaces that will grow his network and skillsets will benefit his personal growth and could contribute to the development of exciting new innovations in healthcare.

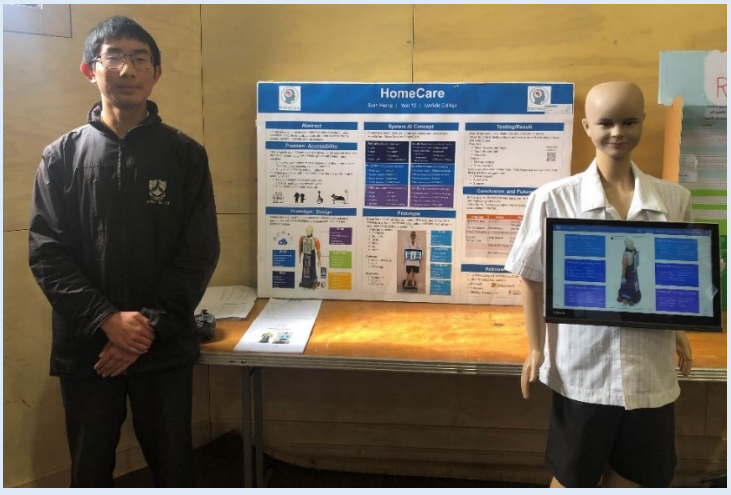


Figure 4: Evan Huang and HomeCare at the NIWA Auckland Science Fair 2023

5.2.3.AI-enabled sensing technology

In a clinical encounter there is a lot of health data that has to be collected, which can be time consuming. Using sensing technology coupled with AI to collect this data could be beneficial, for example by enabling remote medicine. During a video consultation, a patient may or may not have the equipment to measure their vital signs (e.g., blood pressure, heart rate, and temperature) accurately at home. Sensing technology could be used to collect vital signs accurately at home during a video call. This application of AI has so far reached proof-of-concept stage. [132]

Another application of AI-enabled sensing technology is in the management of triage in an emergency department. Standard practice is for vital signs to be recorded on arrival, and updated periodically while the patient waits for a doctor. This process is time consuming for staff and may not be suitably responsive to sudden changes in a patient's condition. Continuous monitoring of vital signs using AI-enabled sensing technology potentially frees up staff time and allows dynamic reprioritisation of waiting patients. This application is in early stages of development in Canada. [133]

Continuous monitoring of vital signs potentially frees up staff time and allows dynamic reprioritisation of waiting patients.

Case study 7: Viz.ai

Viz.ai was founded in 2016 with the aim of utilising AI to make healthcare faster and smarter. The products use AI to accelerate care co-ordination as clinical workflow delays can often impact patients from receiving lifesaving treatment. [134]

Viz.ai has developed clinically-validated products across:

- Medicine: neurological diseases, cardiovascular and vascular medicine, image processing and analysis in radiology
- Communications: streamlining communications in trauma centres, and multidisciplinary specialist follow up

These are being used by over 1400 hospitals across the US and EU. [135] Multiple platforms have received 510(k) clearance, and the CE mark for stroke care software. [136,137]

One example is in caring for stroke patients. For stroke care pathways in clinical practice, one study found that other than a lack of resources (inpatient beds, ambulances, and staff), poor communication and co-ordination among healthcare professionals and facilities were barriers to quality of care. [138] Such inefficiencies are particularly critical for stroke patients where 'time is brain'. [138] One 2023 study found that the Viz.ai care co-ordination contributed to a decrease in notification time from door to specialist[139] and optimised workflow with the potential to improve patient outcomes. [140]

5.2.4.Computer vision

Computer vision refers to machine perception of visual images. [95] AI tools have been trained to find patterns in medical images such as X-rays, CT scans, retinal scans, and mammograms in order to perform clinical tasks such as screening, diagnosing, detecting, monitoring, and predicting patient outcomes. Computers are better at pattern recognition than humans, and human accuracy in interpreting medical images varies both between and within individuals. [141,142] Moreover, interpreting these images is time consuming for clinicians, while computers are able to analyse them and provide an output much faster. There are many examples where AI tools are as accurate as experts at classifying images. [95] These tools could be used to review images and identify anomalies for expert human review, increasing the overall speed and accuracy of the process.[i] A trial which replaces one of two human screeners with AI in breast cancer screening shows promising interim findings, [143] although it is too early to draw conclusions.

Computers are better at pattern recognition than humans, and human accuracy in interpreting medical images varies both between and within individuals.

Another example of the potential for computer vision comes from the field of gastroenterology where AI is improving the practice of colonoscopy and endoscopy. [144] Existing applications include:

- Distinguishing between benign and malignant polyps, avoiding the need for biopsy
- Predicting the depth of cancer into tissue
- Identifying flat gastric cancer; without assistance there is considerable variation in clinicians' ability to confirm that all the relevant landmarks have been visualised
- Signalling whether withdrawal of the scope is happening at an appropriate speed

Further examples of the use of computer vision are detailed in our case studies on retinal screening (case study 8) and mammography (case study 2).

[i] Note that this will require an established and accepted evaluation framework to test claims of increased speed and accuracy of image processing.

Case study 8: THEIA

THEIA is registered as a medical device in New Zealand that commercialised out of the Auckland Bioengineering Institute (ABI). THEIA focuses on screening, diagnosis, and prognosis of diseases like diabetic retinopathy, cataracts, and maculopathy through retinal imaging that can be carried out at pharmacies, optical outlets, or at the GP. It also can map out individualised vision deterioration rates and diseases progression risk. The platform is trained using available images of various diseases and has the potential to reduce the cost of retinal cameras, IT support, and resources of trained clinicians to read images. The tools developed could be particularly useful to increase access to screen diseases in remote or lower socio-economic areas where access to specialist facilities is challenging. Their AI platform is registered as a medical device in New Zealand and looking to expand in the US and Japan, but it is yet to be cleared for sale[145].

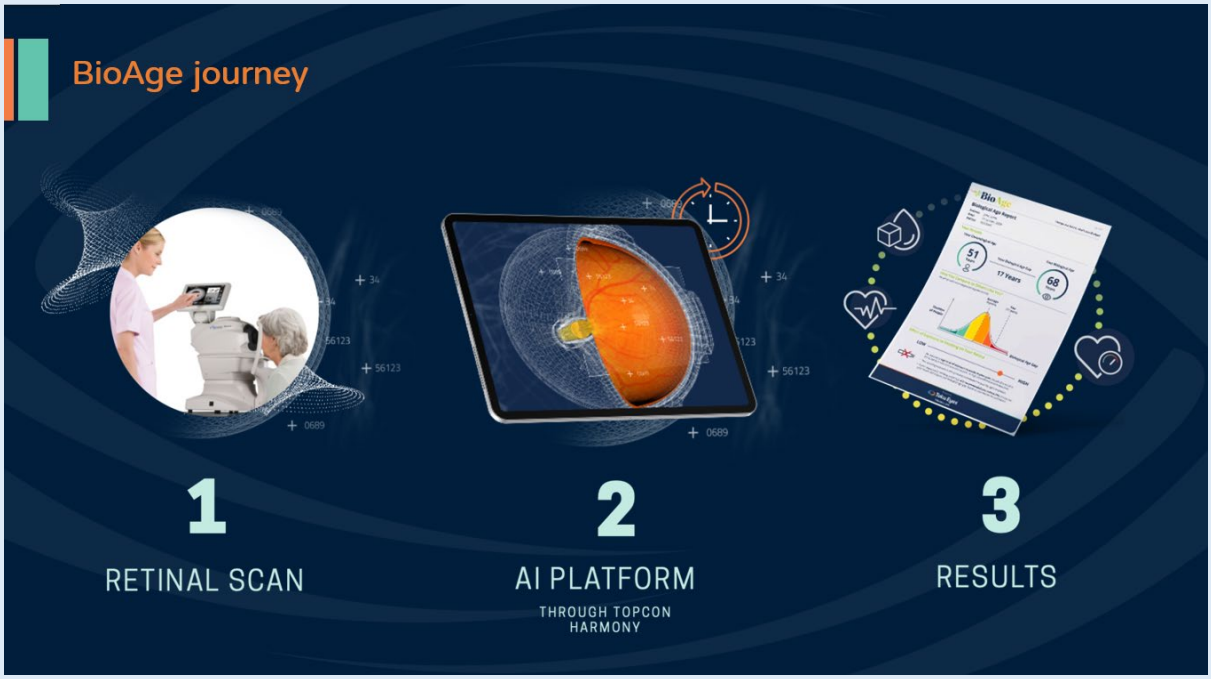


Figure 5: Image supplied by Toku Eyes who use THEIA in their technology

5.2.5. Generative AI

Generative AI (defined in section 1) creates new content such as text or images using LLMs to process 'natural' languages. Te Whatu Ora's current guidance does not allow the use of generative AI to provide diagnostic information, or for any handling of patient information. [146] Nonetheless, ChatGPT, Bard, and other LLMs have caught the public imagination and suggest a myriad of applications for healthcare providers in the future. [2] With appropriate training and evaluation, it is likely that some generative AI tools could become 'medical grade' and suitable for deployment in medical settings.

Clinical education is one area that can utilise generative AI. Consumer tools such as GPT-4 can create case notes, provide examples of clinical reasoning to produce diagnoses and treatment plans, and engage in Socratic processes to guide students and clinical trainees. [2,147] These capabilities could be

enhanced with tools that were trained on, and have access to, appropriate reference material and with user training in prompt engineering to minimise 'hallucinations'. [147]

Clinicians could also use generative AI to guide diagnoses and treatment plans, in much the same way as clinicians seek input on challenging cases from colleagues. Such AI tools could present differential diagnoses, suggest where further information or tests are needed to form a conclusion, or remind practitioners of the circumstances in which different courses of treatment are called for. If AI tools are trained to be alert for rare conditions, they may well prove more successful in suggesting these diagnoses, as exemplified by Kohane in a chapter describing GPT-4's identification of an endocrine issue in a new-born baby. [2]

Generative AI tools could assist clinicians in accessing and absorbing diffuse clinical information. Before a specialist sees a patient, they need to familiarise themselves with the patient's information, which may be voluminous and stored in multiple systems and formats. The tool could bring this information together into an easy-to-read summary.

Generative AI tools may take many forms including written or audio chatbots, or avatars. There is potential for such tools to interact directly with patients and their whānau, increasing the information and support they receive without adding to the demands on clinician time. Low-risk applications of these tools could remind patients of a medication schedule according to their clinician's directions or signpost the availability of clinical and social services. These tools could provide some forms of clinical information and advice on when to seek medical attention. AI tools could also help patients and their whānau in understanding their conditions and consenting to treatment – this could be through asking the AI questions directly, or clinicians could use AI tools to provide information in a way that is easier for patients to understand and tailored to their level of health literacy and preferred language. [2] Finally, some patients interacting with generative AI employed as 'digital humans'[i] (case study 9) may perceive less judgement and therefore be better able to discuss sensitive health topics more freely than they would with a human. [108,148]

Some patients interacting with generative AI employed as 'digital humans' may perceive less judgement and therefore be better able to discuss sensitive health topics more freely than they would with a human.

Taking a meta-view, generative AI makes the work of AI development easier. Predictive AI and other tools that would previously have taken world-leading programmers months to develop can now be built in days by local data scientists, [149] including those in a given hospital, Te Whatu Ora or Manatū Hauora. This reduces the financial and human resource cost of innovation, making it possible to build bespoke tools to meet local needs, or to locally fine tune tools imported from elsewhere.

At present generative AI tools do have limitations and are susceptible to making mistakes. However, the development of appropriate evaluation frameworks coupled with robust policy and legislative settings to inform where and how generative AI should be used could, in time, enable such technologies to augment and support the work of healthcare staff.

[i] We note that not all digital human use generative AI. Some digital humans may make use of other technologies such as dialogue systems.

Case study 9: Soul Machines

It's crucial that AI health applications maintain the human element of healthcare (as noted in our Theme 2 recommendations). But for areas of healthcare where AI is appropriate to use, it may sometimes be beneficial for the AI to be *humanlike*, in its interface with the user. People are used to interacting with other people, so if an AI system is engineered to look and behave like a human, this can support more intuitive interactions with human users and create better rapport. It is of course vital that users can clearly distinguish between humanlike AI agents and actual humans but if this condition is met, humanlike AIs may have considerable uses in health.

Soul Machines was founded in 2016, to commercialise research in Mark Sagar's Lab in the ABI. The company develops 'Digital People', whose faces and bodies are simulated by cutting-edge computer graphics and animation methods, [150] and whose behaviours emerge from a biologically-inspired model of cognition. [151,152] A particular focus is on building appropriate facial expressions and humanlike behaviours during conversations in order to engage users and motivate healthy behaviours. Agents of this kind have potential applications in telemedicine, for instance to address loneliness and [153,154]stress and more generally to provide emotional support and increase trust. Emotional burnout is an acknowledged problem for human health professionals, that grows as workloads increase (as the COVID-19 pandemic demonstrated). AI systems may be able to supplement human care, by performing screening, monitoring, and the delivery of remote interventions[155]. Soul Machines recently partnered with MBIE to offer three Catalyst grants exploring uses of Digital Humans in healthcare.[i] The three selected projects target applications in mental health, support for people with autism spectrum disorder and chronic metabolic disease.

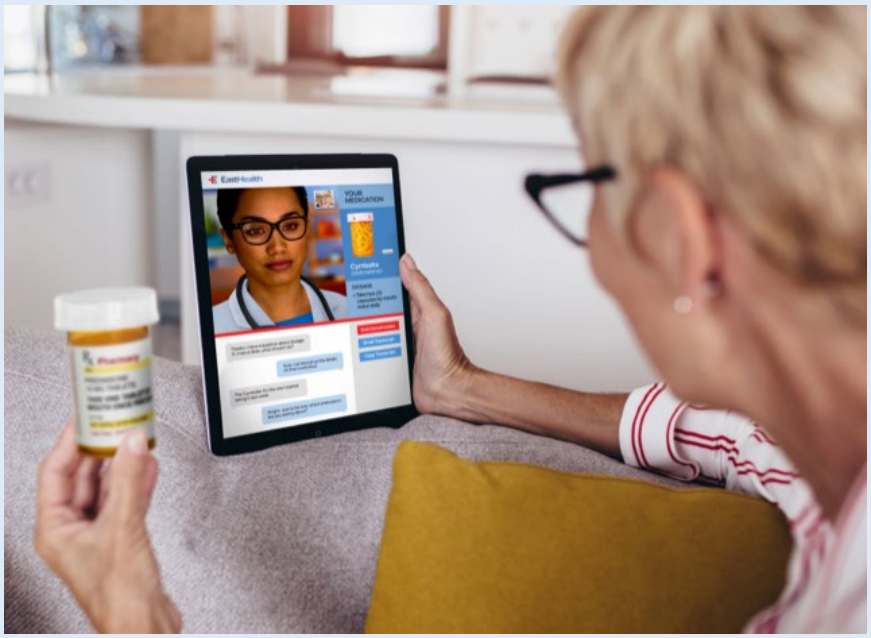


Figure 6: Image supplied by Soul Machines

[i] Details of MBIE funding can be found at https://www.mbie.govt.nz/science-and-technology/science-and-innovation/funding-information-and-opportunities/investment-funds/catalyst-fund/funded-projects/catalyst-strategic-investment-in-health-related-a-i-research-in-partnership-with-soul-machines/

There is the potential that members of the public may seek information from AI applications such as GPT-4. We experimented with this use. The following text is an example of an interaction with GPT-4, seeking advice about a sprained ankle. The generated text has not been edited. Our user prompts are captured in italics and the remainder of the text is the generated output.

GPT-4 cautions the user that it is not a medical professional, which is important in light of the current lack of medical grade AI. Our prompt requested questions to ask the doctor during consultation, and GPT-4 presents a range of possible questions that a patient might find helpful to discuss. The inclusion of this excerpt is not intended to advocate for the immediate deployment of LLMs within healthcare settings; however, it does provide a glimpse of current capabilities and the type of generated content that might be found in our local context.

I rolled my ankle on uneven ground, and it is now swollen. I can bear weight on part of my foot but not the whole foot. The pain is dull, constant and mainly towards the heel. I have no bruising and can still move my foot. Can you explain what I might have injured and what questions I should ask my doctor in New Zealand?

I'm not a doctor, but I might be able to help guide you with some general information. Rolling an ankle can lead to various injuries such as sprains, strains, or fractures. Since you're experiencing swelling and pain, it's essential to consult with a healthcare professional or a physician for an accurate diagnosis and appropriate treatment.

Possible Injuries:

Ankle Sprain: Overstretching or tearing of the ligaments in the ankle. Ligaments are the tissues that connect bones to each other.

Strain: Injury to the muscle or tendon.

Fracture: A break in the bone, which can range from a hairline fracture to a complete break.

What You Can Do Until You See a Doctor:

Rest: Avoid putting weight on the affected ankle as much as possible.

Ice: Apply ice wrapped in a cloth for 15-20 minutes every 1-2 hours for the first 48 hours.

Compression: Wrap the injured ankle with a bandage to help reduce swelling.

Elevation: Keep the ankle elevated above heart level whenever possible to minimize swelling.

Questions to Ask Your Doctor:

Diagnosis: What specifically is the injury? Is it a sprain, strain, fracture, or something else?

Severity: How severe is the injury? If it's a sprain, what grade is it?

Treatment Options: What are the recommended treatment options? Is surgery necessary?

Recovery Time: How long will the recovery process take?

Physical Therapy: Will I need physical therapy or rehabilitation? Can you recommend exercises or activities to aid recovery?

Weight-Bearing: When can I start putting weight on the ankle again?

Pain Management: What can I do to manage pain and swelling?

Prevention: How can I prevent this injury from occurring again in the future?

Follow-up: Do I need a follow-up appointment or further imaging like an X-ray or MRI?

Important Note:

Since I am not a medical professional, and this isn't a substitute for professional medical advice, diagnosis, or treatment, please consult with your local healthcare provider, GP, or an orthopedic doctor in New Zealand for an accurate diagnosis and treatment plan based on your individual health condition.

This is also consistent with the advice you would receive from Healthline, the New Zealand public health advice line, which advises seeing a doctor for any persistent or severe symptoms. If you find it difficult to see a doctor promptly, consider reaching out to a registered nurse via Healthline at 0800 611 116 for advice on managing your symptoms until you can be seen.

5.2.6. Opportunities for research

AI has the potential to dramatically increase our capabilities in health research. Much basic research involves time consuming or computationally demanding tasks and in these domains AI is likely to transform the rate of discovery. A recent reflection from Australia's Commonwealth Scientific and Industrial Research Organisation highlighted the transformational aspects of AI for speeding up slow and labour-intensive tasks such as counting objects/ features and repetitive image analysis, [156] as described for the practice of radiology (case study 2). Such developments underpin discovery in cell biology which is likely to benefit from similar disruptive technology advancements. [157]

In terms of day-to-day research practice, AI is also likely to transform basic literature analysis and the communication of research. Given an abstract and section headings, generative AI tools have been shown to efficiently produce a first draft of a traditional journal article. [158] Generative AI tools could also be useful for increasing the impact of research, by creating outputs tailored to specific audiences for whom journal articles are not accessible or useful.

Beyond speeding up the execution of today's science, AI is poised to change the way we think about discovery. A recent review article in Nature captures likely contributions that AI may make in the practice of science, several of which have direct relevance to medicine (figure 7).[159] AI can not only speed things up, but also enhance the design and execution of scientific experiments across disciplines, with a particular role to play in generating hypotheses which can be experimentally tested.

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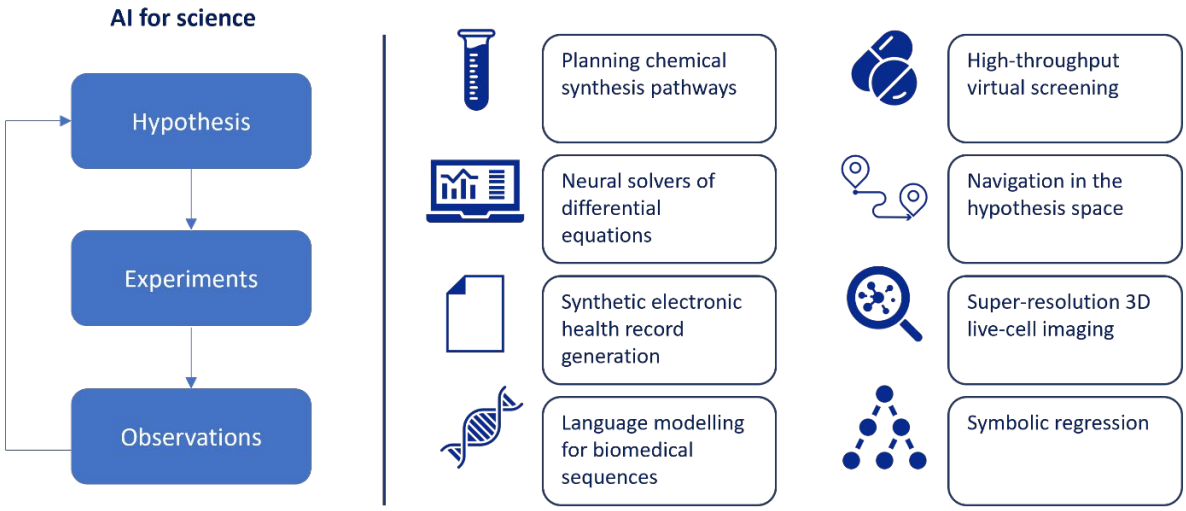

Figure 7: The principles and illustrative studies shown here highlight the potential contributions to enhance scientific understanding and discovery. (Figure adapted from Wang et al., 2023)

The most dramatic example to date is perhaps in protein folding. Protein scientists have long known that the information required to fold a protein into its precise three-dimensional structure is encoded in its amino acid sequence, but the so called 'protein folding problem' was a grand challenge which was not solved by humans over five decades. [160,161] In a breakthrough study in 2021,[152] deep learning using AlphaFold, software first presented by Google's DeepMind in 2018,[153] was shown to be able to solve the structure of proteins using only sequence information with a high degree of accuracy when compared to structures solved by experiment. AlphaFold2 incorporated novel neural networks and training procedures built on known evolutionary, physical and geometric constraints of protein structures, [162] and has generated millions of protein models, freely available in the AlphaFold Protein Structure Database hosted at the European Bioinformatics Institute–European Molecular Biology Laboratory (EMBL-EBI), which also provides tools to interrogate the structures. [163] Improvements continue to be made at a rapid pace by this and other AI tools, including addressing the harder problem of solving the structures of protein complexes. This work has huge downstream implications for biomedical researchers.

In addition to providing leads for targeted drug design, AI also opens up rapid exploration of large possibility spaces. For example, it has been estimated that 10^{60} drug-like molecules exist, [156] far beyond the limits of physical screening methods. Using AI to predict which of these molecules might inhibit a drug target shows promise for orders of magnitude acceleration of drug discovery, [164,165] with hints that this is already opening new avenues for effective medicines.[159]

Another recent example of the potential for AI to enhance our health research capabilities is in the discovery of antivirals. One recent publication describes how a generative AI called CogMol was trained on general information about proteins and their binding properties. [166] Researchers found that the model was able to identify potential antivirals for the COVID-19 virus. Discoveries of this nature offer exciting glimpses of the future potential of medicine.

In addition to providing leads for targeted drug design, AI also opens up rapid exploration of large possibility spaces.

AI is also demonstrating considerable promise in genetics and genomic-wide association studies, [167] where it can support decoding of complex data sets and provide hypotheses for biological insights into mechanisms of disease. As the power of these tools grow, understanding potential biases within the tools and addressing ethical concerns will become increasingly crucial, underscoring the importance of a principled base to the use of AI in medical research and medicine more widely (see section 2). Nevertheless, the potential of genomic information being used in partnership with medical practitioners to quickly narrow down differential diagnoses is enormous, [2] with new possibilities emerging almost daily in the research literature.

The capacity of AI to work across research fields opens up opportunities to integrate different omics technologies by supporting standardisation of information across data sets, collection and analysis of data, computational infrastructure with which to interrogate the data and advanced methods to improve interpretability. The possible applications of this integration are many, as illustrated by a recent review of using this approach for precision oncology[168] and a recent Science article highlighting the progress made in using AI to help control infectious diseases and pandemics. [169]

Ensuring effective channels of communication between the health sector, universities, the private sector, and CRIs can drive innovation targeted to local needs. Institutions are working toward building their capabilities to build and apply AI. As yet these efforts are not well co-ordinated and would benefit from integration and resourcing for collaboration and multi-disciplinary research and innovation. Our team has developed a select snapshot of some of the research capabilities in our CRIs and universities (Annex 4).

Ensuring effective channels of communication between the health sector, universities, the private sector, and CRIs can drive innovation targeted to local needs.

5.2.7. Looking ahead

AI technology is advancing rapidly, meaning that there will be new developments that could bring benefits to health. It would be useful for horizon scans to be performed at regular intervals to capture new advances and opportunities for Aotearoa New Zealand.

Case study 10: NeuCube and Te Ara Poutama ō Tāwhaki | NeuroGeMS

Te Wānanga Aronui o Tāmaki Makau Rau | Auckland University of Technology (AUT) has been experimenting with AI since 2000 (see Annex 4). An early output through its Knowledge Engineering & Discovery Research Innovation (KEDRI) team is NeuCube, a Brain-Like AI (BLAI) that has been in development since 2014 and is modelled on how the human brain learns and recognises patterns. The platform utilises Spiking Neural Networks (SNN).

There are potential applications across various domains, including healthcare. For example, the KEDRI team recently received MBIE Catalyst funding to support an international collaboration which uses Singaporean data to train AI to predict psychosis, enabling early clinical intervention.

One output of the MBIE funding is Te Ara Poutama ō Tāwhaki |NeuroGeMs[i], a neuro-genetic multimodal system that specialises in explainability and interpretability. [20] NeuroGeMs enhances machine learning with useful features that include: [170]

- Multimodal fusion - enabling data integration from diverse sources and modalities
- Interpretability - the ability to analyse and explain model decision-making, enhancing model transparency
- Data visualisation – interactive data visualisation tools that enhance understanding of insights and communication of findings

[i] https://www.mbie.govt.nz/science-and-technology/science-and-innovation/funding-information-and-opportunities/investment-funds/catalyst-fund/funded-projects/catalyst-strategic-new-zealand-singapore-data-science-research-programme/

6. CONSIDERATIONS FOR OUR AOTEAROA NEW ZEALAND CONTEXT

Prompt: A painting of a futuristic nurse in rural New Zealand. Created using Stable Diffusion on huggingface.co

Key messages

- While addressing the complexities that sit at the intersection of mātauranga Māori and AI are beyond the scope of this report, we recognise some of the historic and ongoing kaupapa whose outcomes intersect with the delivery of healthcare services. We also acknowledge that the Crown has obligations under Te Tiriti o Waitangi which extend to the delivery of healthcare services
- Beyond the technical capabilities of AI tools, there are various societal factors that will need to be considered by decision-making bodies. Fully articulating and addressing these social factors goes beyond the scope of this report however we highlight issues of public trust, clinician trust, and education as broad areas for ongoing consideration
- Our ability to access the benefits that AI has to offer will depend to some extent on having suitable data for development, training, and fine tuning of AI tools. The digitisation of our health records is underway and we would benefit from this work continuing to keep pace with our international peers
- One of the enticing possibilities that AI offers is the potential to address various health equity issues if trained on appropriate data sets and with goals aligned to our desired equity outcomes

6.1. Te ao Māori

In general, strong data protection practices and policies are essential tools for maintaining public trust. For Māori, data are a taonga, necessitating models of care and protection that are culturally grounded. [171] While identifying solutions to address issues of significance to tangata whenua as treaty partners is beyond the scope of this report and beyond the mandate of its authors, we take this opportunity to recognise some of the historic and ongoing kaupapa whose outcomes intersect with the delivery of healthcare and the wellbeing of tangata whenua in Aotearoa New Zealand. The framing of the collective is useful to inform wider issues arising from the challenges AI presents in linking individualised health data.

6.1.1. Te Tiriti o Waitangi

Te Tiriti is a founding document of government in New Zealand. [172] The principles of Te Tiriti are largely concerned with the relationship between Crown and Māori and present important considerations for decision-making. As a key source of New Zealand's constitutional framework it is likely that constitutional, legal, ethical and procedural issues related to Te Tiriti will continue to be discussed, and debated, in various settings.

Te Tiriti[i] imposes on both tangata tiriti and tangata whenua an obligation to act toward each other reasonably and with good faith.[ii] Based on the exchange of kāwanatanga, Te Tiriti establishes the right for the Crown to govern and make laws and for Māori to exercise tino rangatiratanga over their

[i] While te Tiriti is sometimes referred to as the founding document of Aotearoa, matters of sovereignty had already been addressed prior to its drafting and signing. *He W[h]akaputanga o te Rangatiratanga o Niu Tireni (He Whakaputanga)* asserted the sovereignty and mana of its signatories and was acknowledged by The Crown. [173, 174.] It is argued by some that without He Whakaputanga, te Tiriti may not have eventuated.

[ii] *New Zealand Māori Council v Attorney General* [1987] 1 NZLR 641

lands, resources, and people. As such there should be mechanisms in place that allow for Māori to manage their affairs in accordance with their own customs and values. [175,176]

> As a key source of New Zealand's constitutional framework it is likely that constitutional, legal, ethical and procedural issues related to Te Tiriti will continue to be discussed, and debated, in various settings.

More recently the judgement of the Supreme Court recognising tikanga Māori as common law and applicable in the legal system reinforces the need to reflect on principles of Māori Data Sovereignty, their enactment and consideration for how these give effect to our obligations under Te Tiriti.[i] With technological advancement and the increased availability of AI tools that might be implemented into our healthcare ecosystem, it is important that ongoing consideration be given to the necessary tikanga for the handling of Māori data.

6.1.2. The United Nations Declaration on the Rights of Indigenous Peoples

The United Nations Declaration on the Rights of Indigenous Peoples (UNDRIP) recognises and reaffirms collective rights for Indigenous populations and is endorsed by the New Zealand[177] government. Māori data sovereignty is consistent with collective rights outlined in the UNDRIP report.

6.1.3. Wai 262

The history of what is now referred to as the 'Wai 262' claim stretches back to 1991 when six claimants sought protection for taonga Māori by tangata Māori. Now commonly known as the Flora, Fauna and Intellectual Property Rights Claim, Wai 262 will form the basis for the protection of taonga and mātauranga Māori throughout the motu. In July 2023, Wai 262 launched 'Tiaki Taonga' which, in time, is intended to become the legislative framework that was sought by the original Wai 262 claimants three decades ago.[ii] While establishing a complete framework will take time, there is no doubt that the outcomes of this process will have significant implications on many government agencies, likely impacting on the collection, definition, storage, and use of Māori data.

6.1.4. Wai 2522

The Wai 2522 report on the comprehensive and progressive agreement for trans-pacific partnership discusses matters of Māori data, Māori data sovereignty and Māori data governance. [179] The report does not define what Māori data is but instead considers whether Māori data is – or has the potential to be – a taonga. The tribunal found that data can record mātauranga - which is a taonga - and that mātauranga is capable of informing and generating data. While the tribunal are not able to determine whether all data are taonga, the potential for data to be a taonga has implications for our treaty partnership, requiring the Crown to protect the rights and interests of Māori. The tribunal

[i] *Peter Hugh McGregor Ellis v R [2022] NZSC 114.*

[ii] A series of engagements are set to take place across the motu with input sought from whānau, hapū and iwi to inform the framework. In parallel, technicians and practitioners will work to establish legislation on Indigenous intellectual property protection. [178] Sheridan Waitai, Wai 262 Whakapūmau members asserts that "Tiaki Taonga is about constitutional change to fully recognise kaitiakitanga of taonga and mātauranga by Māori, for Māori…when the use of taonga and mātauranga Māori are being considered, te iwi Māori will have exclusive authority over their use." [178]

found that data can record mātauranga (which is a taonga), and that mātauranga is capable of informing and generating data.

6.1.5. The Hauora report

The Wai 2575 inquiry was confirmed to proceed in a staged approach in December 2017. [180] Health-related issues were heard according to priority and in May 2023 the Waitangi Tribunal released *Hauora: Report on Stage One of the Health Services and Outcomes Kaupapa Inquiry.* [181] The Tribunal identified that the Crown breached its obligations under Te Tiriti, failing to actively address persistent Māori health inequities and failing to give effect to the guarantee of tino rangatiratanga.

The Hauora report highlights a lack of quality data. [181] While there is sufficient evidence to demonstrate inequitable health outcomes for Māori, there are limitations. [181] Detailed Māori health data, and performance data from health entities is not easily accessible and in many cases is not available at all (health equity is discussed further in section 6.4). This has implications for setting appropriate Māori health targets and will require addressing for the Crown to fulfil its obligations as a treaty partner. [182]

6.1.6. Te Kāhui Raraunga Māori data governance model

In 2023 Te Kāhui Raraunga released the *Māori data governance model.* [22]The model was developed from a partnership between the Data Iwi Leaders Group and Stats NZ and establishes a framework for the governance of Māori data providing direction on the actions, processes, and activities necessary to realise these expectations. Establishment of the framework involved extensive consultation over more than two years. The report describes the term 'Māori data' as referring broadly to "digital or digitisable data, information or knowledge (including mātauranga Māori) that is about, from or connected to Māori. It includes data about population, place, culture, and environment." [183] Māori data is often discussed in the context of Māori data governance and Māori data sovereignty. The former refers to "the processes, practices, standards and policies that enable Māori, as collectives and as individuals, to have control over Māori data." [183] The latter refers to the "inherent rights and interests that Māori have in relation to the collection, ownership and application of Māori data." [183] Te Kāhui Raraunga emphasises collective data rights, in contrast to current health standards which focus on the individual. We heard in our engagements that work continues to resolve the tensions between individual and collective rights within te ao Māori. [171,184] It is likely this framework will play a key role for decision makers with the ongoing deployment of AI in healthcare.

> Te Kāhui Raraunga emphasises collective data rights, in contrast to current health standards which focus on the individual.

6.2. Fit-for-purpose AI

AI has the potential to benefit a wide range of healthcare professionals including, but not limited to, doctors, nurses, allied health professionals and administrative support staff. For example, development of biomechanical models could support decision-making processes of orthopedic surgeons (case study 11). Another example is the nursing profession where LLM applications could assist nurses in monitoring and confirming drug administration, triaging, and optimising patient

logistics.[2] Where activities can be augmented by AI, nurses can continue providing the genuine care and human presence patients need.[185] As new AI tools emerge with the potential to support our healthcare workforce, it is important that decision makers are aware of the stresses and strains that exist within our current workforce to understand where pressures could be alleviated to the greatest effect.

AI has the potential to benefit a wide range of healthcare professionals including, but not limited to, doctors, nurses, allied health professionals and administrative support staff.

Our local needs will also determine the extent to which emergent AI technologies are fit for purpose. The extent to which benefits are realised within our healthcare system will depend largely on the characteristics of the AI tools that are deployed. It is important that decision makers choose to develop or adopt AI tools for deployment that meet our contextual needs, rather than simply deploying tools that are generating momentary hype. Determining the appropriateness for deploying AI tools into our national healthcare services will require decision makers to have readily available evaluation frameworks that consider factors beyond technical efficacy.

It is important that decision makers choose to develop or adopt AI tools for deployment that meet our contextual needs, rather than simply deploying tools that are generating momentary hype.

Case study 11: Formus Labs Ltd.

Founded within the ABI, Formus enhances surgical decision-making processes to improve patients' lives worldwide. Developing biomechanical models of the hip joint generally relies on limited geometric information available through traditional medical imaging techniques. [186] Minor changes to model geometry have implications on subsequent joint force calculations, a crucial factor to understand for hip arthroplasty implant mechanics. [187] Employing cutting-edge biomechanics and AI-enabled machine learnings, Formus Labs' Automatic Custom Implant Design (ACID) can establish an exact 3D model of the hip joint that enables surgeons to map out surgical interventions virtually and can produce a plan from a scan in under an hour. Feedback from orthopedic surgeons describes how "the Formus platform helps showcase all available options, assisting with decision-making on the best possible reconstruction for the patient." Formus received its 510(k) clearance from the FDA as the first automated radiological image processing software, allowing the company to grow internationally. [188]

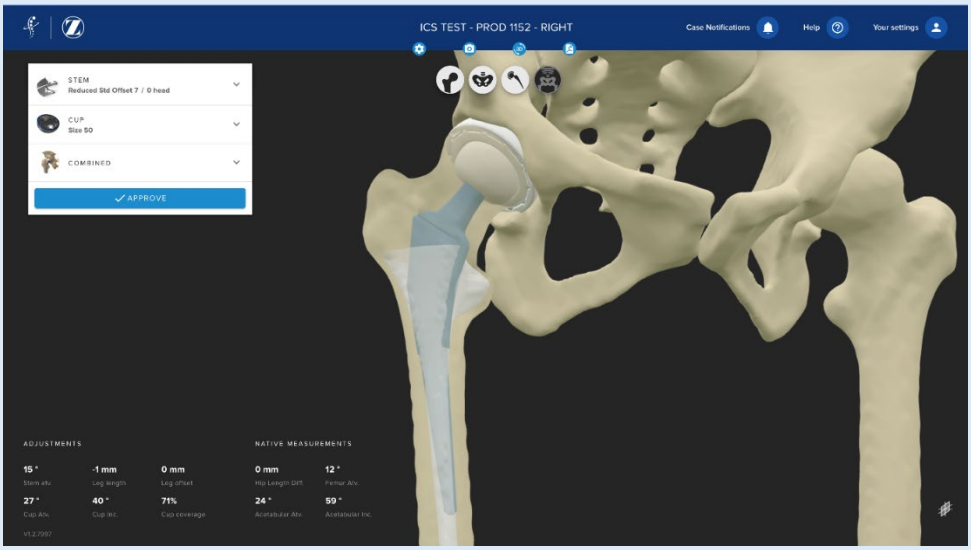

Figure 8: Image supplied by Formus Labs

Figure 9: Image supplied by Formus Labs

6.2.1. Evaluation frameworks

Deploying AI systems into healthcare settings has the potential to be expensive and disruptive. A robust evaluation framework to support decision-making is essential to ensure that translation into real-word practice is as smooth as possible. [23,189] While decision makers must consider the outcomes of technical evaluations and audits of AI applications (i.e., does the technology do what developers claim it can do and meet necessary performance metrics), considerations should also be made for the broader workflows that the AI will be implemented within and the extent to which deployment supports or enhances healthcare delivery. We heard through our engagements that some AI tools available at present have not yet matured to the level of sophistication and clinical utility to be ready for application in healthcare settings. Stakeholders stressed that it is key for decision makers to be able to distinguish between AI tools that have clinical utility and those that do not.

> It is key for decision makers to be able to distinguish between AI tools that have clinical utility and those that do not.

Several frameworks are published for evaluating AI applications. [190-192] Importantly, Reddy et al. noted that many of the available frameworks focus on reporting and regulatory aspects, neglecting to consider functional utility and ethical dimensions such as privacy, non-maleficence and explainability. [192] The authors highlight a need for an evaluation framework that assesses the various stages of product development, deployment, integration and adoption of AI systems. The Translational Evaluation of Healthcare AI (TEHAI) framework was developed in response to this.

> Many available frameworks focus on reporting and regulatory aspects, neglecting to consider functional utility and ethical dimensions such as privacy, non-maleficence and explainability.

The TEHAI framework consists of three major components (capability, utility, and adoption), each consisting of various subcomponents that can be scored and weighted at the discretion of decision makers. [192] Reddy et al. posit that the TEHAI framework overcomes the narrow focus that is built in to many existing frameworks where the emphasis may be placed on a specific medical domain or comparison with human clinicians for example. The research highlights the significance of ensuring mechanisms to evaluate AI tools pre- and post-deployment throughout the AI lifecycle to identify potential concerns, challenges, or issues with a given tool. Evaluation should encompass the full development process and will ideally be ongoing to ensure a suitable fit in the healthcare environment.

We highlight the TEHAI framework as an example of the multiplicity of factors that decision makers will need to consider. Consideration of our national context should inform the decision-making frameworks we adopt. Locally, Te Whatu Ora's NAIAEAG has developed an evaluation checklist for the validation or implementation of a new AI. [15] High level evaluation themes are listed below:

- AI algorithm/model
- Consumer engagement and perspectives
- Development process
- Equity and fairness issues and mitigations

- Implementation plan
- Māori engagement and perspectives
- Monitoring and audit plan
- Other approvals
- Product purpose
- Team
- Testing and validation
- Use of AI in practice

The framework is captured in full in Annex 2.

6.3. Wider societal considerations

There are various social factors that will be impacted by the deployment of AI technology in healthcare settings now, and into the future. These social factors are beyond the scope of our report however we have opted to highlight issues of public trust, clinician trust, and education as broad areas for ongoing consideration. Factors such as cultural values systems and cultural safety will also be useful to consider and have been captured, in brief, in Annex 6.

6.3.1. Public trust

As the use of AI in healthcare provision increases, mechanisms to assess social license around the use of AI are necessary to ensure public trust is maintained. An Ipsos survey *Global Views on AI in 2023* shed light on public perceptions and attitudes towards AI across 31 countries.[193] While the survey is not specific to healthcare services, results indicate that New Zealand survey participants demonstrate lower levels of trust than the global average. Asked whether the increased use of AI will make individual health better or worse in the next three to five years, 31% of respondents from New Zealand indicated that they feel health will be much better or somewhat better, compared with a global country average of 39%. The samples used to generate these results are not necessarily representative of the populations from which they are drawn, however, the results provide us with some understanding of the public perception of AI and its impact on day-to-day life upon which to build.

Asked whether the increased use of AI will make individual health better or worse in the next three to five years, 31% of respondents from New Zealand indicated that they feel health will be much better or somewhat better, compared with a global country average of 39%.

While data-driven algorithmic approaches to support clinical decision-making have been in use for some time, the recent emergence of LLMs has generated significant public excitement with much speculation around AI's potential impact.[194] This has also raised questions about whether to trust AI, especially in sensitive domains such as healthcare. If public trust is harmed during the process of AI development and/or deployment, this could have negative impacts on the health sector generally and might impact on social licence for data to be used moving forward. For healthcare delivery in New Zealand, there is an opportunity to capitalise on real benefits while mitigating risks and avoiding over-hyped promises of the future. Effective communication strategies that propagate

targeted information about AI technologies, including evaluation results, may help to build and maintain public trust over time.

The availability of individual-level patient data holds significant potential for research and healthcare practice, and access to large-scale health data sets are essential for the development of machine learning and AI supported tools (see section 6.4 for potential data sources). As the demand for access to these data sets grows there is a need to understand how patients prefer their health information to be accessed and used, and for patients to understand the benefits to their communities by including their data in the data sets that are used to train AI tools. International research indicates that in general there is public support for the use, and secondary use, of health information under the condition that the use serves the 'greater good'. [195-197] These findings are echoed in New Zealand where healthcare consumers express general comfort with the health service using de-identified health information. [198,199] A 2022 cross-sectional survey found that while a majority of the public appear comfortable with the use of their personal health data, a number of survey respondents were uncomfortable with their data being used due to a mistrust in the health systems or services. [200] Further, some expressed a desire to provide specific consent for their data.[i]

It is important to recognise that public support for use of health data is not unconditional. Maintaining public trust and support is related to the assurance of data use being for public good, secure data storage, and the maintaining of individual privacy and transparency with how data are used. [198] In the public sector, New Zealand's *Algorithm Charter* was one of the first in the world to provide guidance on how government could use individual data and was intended to build public trust in data collection and use by government ministries and agencies, although improvements are still needed to fully recognise Te Tiriti. [198,200-202]

> Maintaining public trust and support is related to the assurance of data use being for public good, secure data storage, the maintaining of individual privacy and transparency with how data is used.

6.3.2. Clinician trust

Like patients, healthcare practitioners must trust the tools that they adopt into clinical settings. [203] In our engagements, we met clinicians who expressed their own and their colleagues' varying levels of trust in AI tools. [203] We can categorise these broadly into three positions: low trust, open-minded, and high trust. People who had low trust did not expect that AI could benefit them and were reluctant to consider using them in their practice. People who were open-minded were not generally using AI tools in their practice, but thought it was possible such tools may be of benefit to their practice in the future. People with high trust were enthusiastic advocates for AI, generally – though not universally – believing that AI tools offered a higher standard of care.

Clinicians are an important stakeholder group and their buy-in will be critical to successful deployment of AI in our health system. It will be important to undertake in-depth engagement with clinicians to understand the factors that contribute to their trust or lack thereof. Without pre-empting such engagement, factors to consider are likely to be the evidence base and evaluation

[i] The survey was sent to 9,215 people from the New Zealand Health Survey mailing list. A total of 2,575 completed the survey.

frameworks for any given tool, systemwide governance structures as discussed in section 4.3, and concerns that AI tools may be used to replace rather than augment clinicians.

6.3.3. Education

AI is likely to transform many aspects of education across all domains. In healthcare, there are several different aspects to consider:

Improving AI literacy of the public

Adequate information needs to be freely available to ensure that the public are informed of the benefits that AI supported healthcare might provide while also being aware of risks and the implications of their data being used to inform AI models. Educational material might include case studies of AI technology, coupled with evaluation outcomes tailored to inform the target audience. The effective communication of the various applications for AI in healthcare might support a shift in public perceptions and attitudes towards AI, generating a greater degree of public trust. [193]

Educational material might include case studies of AI technology, coupled with evaluation outcomes tailored to inform the target audience.

Improving AI literacy of decision-makers and healthcare professionals

While AI provides an opportunity to improve healthcare delivery, our healthcare workforce are essential for implementing tools to realise the benefits. Healthcare professionals in decision-making positions should be aware of the consequences of AI technology to impact health outcomes across clinical settings, and should be sufficiently skilled that they are able to interrogate and potentially challenge the outputs of AI tools. It will become increasingly important to have a workforce that understand AI and how to work with it. [21,204]

To adequately upskill the current and future workforce will require the setting of appropriate training/educational priorities, coupled with building of adequate capability among educators and the development of appropriate content. [204] Providers of professional development might consider developing targeted information for healthcare professionals including allied healthcare workers such as nurses. [205] Appropriate educational material tailored to the right level of specificity will ideally allow for a higher level of trust and AI literacy in our workforce over time. This could look like communications of the outcomes of technology testing and evaluation to establish familiarity with AI tools, to enhance workforce trust, and to support the deployment of AI in healthcare settings. [206]

Appropriate educational material tailored to the right level of specificity will ideally allow for a higher level of trust and AI literacy in our workforce over time.

While formal mechanisms of delivering educational material are important, we note that interdisciplinary interactive situations such as datathons and networking events can provide alternative ways to learn, complimenting or reinforcing content delivered through institutional settings[207]. As such, training providers might also consider establishing forums that allow for multi-disciplinary engagement and networking.

Enabling informed use of AI in medical education

Education providers across all tiers must understand and impart to students the appropriate AI related knowledge to ensure sufficient capabilities.

Tertiary level providers should consider the impact of AI on curriculum design, keeping in mind the rapidly evolving AI landscape and the capability needs of graduate students as they enter the workforce. AI technologies are already disrupting medical education, with tools such as ChatGPT performing at or near a passing grade for the United States Medical Licensing Exam and more recent analyses showing GPT-4 outperforming these results with even greater levels of confidence.[208] This demonstrates the potential for LLMs to assist with medical education and highlights an urgent need to reflect on current mechanisms for medical education and assessment. [96,97] Shifting the emphasis of testing and assessment to problem-solving, professionalism, work ethic, and respect for patients and other medical staff, perhaps in collaboration with AI tools, could prove more useful. [209] The potential opportunities for AI in healthcare education are many, and categorised by Abd-Alrazaq et al. in figure 10.

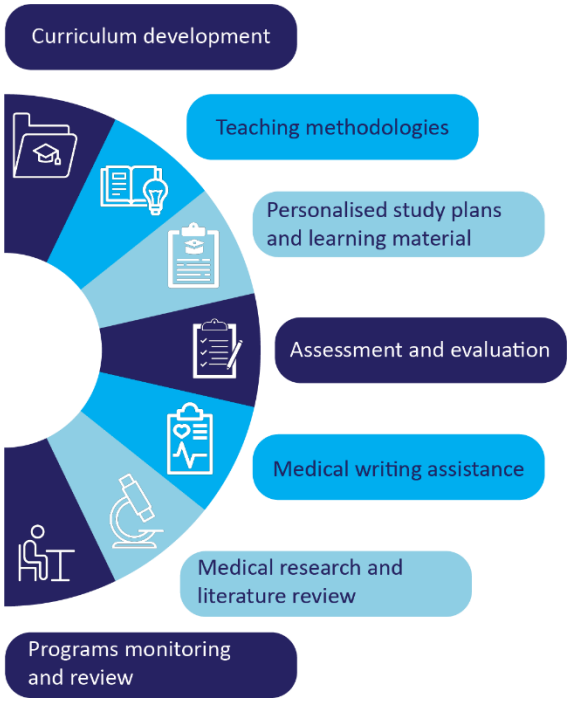

Figure 10: An overview of potential opportunities for AI in healthcare education (reproduced from Abd-Alrazaq et al., 2023)

Globally, conversations around how best to incorporate AI education into medical curricula given the rapidly evolving AI landscape are already taking place. For example, Hu et al. articulated four recommendations for curriculum development following the delivery of AI training material to Canadian medical students. [210] These are:

- Identify core AI competencies in collaboration with clinical experts to understand how AI topics can be applied to clinical workflow
- Create AI case studies that can consolidate abstract concepts
- Use experiential learning such as flipped classroom teaching models to allow students to practice technical skills on their own, allowing class times to be used for problem solving

- Expand to multi-disciplinary participants from across different faculties to reflect lifelike multi-disciplinary workplace interactions

Education providers in our local context should maintain an awareness of global learnings and trends to inform our national approach to AI education.

6.4. Our potential data sources

Our ability to benefit from AI will depend on having suitable data both for the development, training, and fine-tuning of tools and for their actual operation. In this section we summarise the state of our data, highlighting sources that will be valuable for these tasks.

Our ability to benefit from AI will depend on having suitable data both for the development, training, and fine-tuning of tools and for their actual operation.

One of the most important data sources for operating a range of AI tools within the health system will be harmonised electronic medical records. Our system is not there yet. In our engagements, we heard that New Zealand would benefit from committing more resources to implementing electronic health records to keep pace with some of our international peers. The former DHBs each had different systems of data storage and management, and one important task of the recent health system restructure is to harmonise these. We heard throughout the engagement process that this presents a significant hurdle. AI applications for building large-scale electronic health record models using any form of medical data, from distinct healthcare record systems, are under development and could help to address this need in future. [210] For the present moment Te Whatu Ora is undertaking a programme of work called Hira that will fill this gap. Hira will create a personal health record that makes it easy for patients to access their own data, a platform for providers to access and update health information in various databases, and a secure data system for vendors to build apps for deployment in the platform. [211] Individual-level data held by the health system could be used in the development or refinement of AI, as well as being inputs used in its operation and in its ongoing evaluation.

New Zealand would benefit from committing more resources to implementing electronic health records to keep pace with some of our international peers.

Perhaps surprisingly given our progress on electronic health records, in our engagement we heard that in some domains our data are world leading. One example is data from BreastScreen Aotearoa[i] programme, which includes records of every mammogram performed since the programme's inception as well as relevant information about the women involved, and was described by one stakeholder as some of the richest in the world. These sorts of data are potentially valuable for developing AI locally and fine-tuning imported AI tools.

The Integrated Data Infrastructure (IDI)[ii] holds individual level data on anyone who has been a resident in New Zealand. This population is identified by records of births, visas, and taxation, and

[i] https://www.timetoscreen.nz/breast-screening/
[ii] https://www.stats.govt.nz/integrated-data/integrated-data-infrastructure/

can be probabilistically linked to other data held by government agencies including health, education, justice, benefits, and social services. Data held in the IDI could be used in developing and fine-tuning AI tools, and in evaluating their outcomes.

New Zealand has a number of longitudinal data sets that have historically been used by academics for health and social research. These include the Dunedin study,[i] which has followed everybody who was born in Dunedin hospital between 1 April 1972 and 31 March 1973, the New Zealand Health Work and Retirement study[ii] which has followed people aged 55 years and over since 2006, and Growing Up in New Zealand[iii] which has followed young people and their families since before the study member's birth in 2009-10. Growing Up in New Zealand is particularly useful because it oversamples Māori and Pacific children, enabling statistically robust analysis of data from these groups. All of these studies have asked their participants about a broad range of topics over time, making them valuable for understanding a wide range of issues. The data may be able to be used in developing and fine-tuning AI tools, although these studies have relatively small sample sizes compared to other data sources.

Not all useful data are easily available for building, fine-tuning, or using AI tools. For example, data collected by Whānau Āwhina Plunket, the country's largest provider of routine health and wellbeing checks for under-5s, do not become part of the child's health record.[212] This limits the utility of the data in the building and deployment of AI tools, although it may be possible for researchers and others to apply to use Plunket data for post-hoc evaluations of interventions using AI tools.

Considerations related to data availability and use are explored in various parts of this report. See section 6.1 for a discussion of Māori data sovereignty, sections 4.4.1 and 6.3.1 for discussions on public views on data use and consent for using data in AI development, and section 6.5 for the implications of data quality for health equity, and a summary of how data can act as an enabler or a barrier to adoption of AI in our health system.

6.5. Health equity

Principle 9 suggests that adoption of AI is done in a way that promotes health equity. Inequities in health refer to differences in health that are avoidable and unfair. [213,214] In its Pae Ora strategies, Manatū Hauora has laid out its vision for an equitable health system, with specific strategies for priority groups[iv] who are underserved by the status quo: Māori, Pacific people, people with disabilities, rural people, and women. [215-219] Manatū Hauora has developed distinct health strategies for each of these groups, but for our purposes thinking about the ways in which AI could address or exacerbate inequalities, these categories often intersect and compound disadvantage. Any AI tools

[i] https://dunedinstudy.otago.ac.nz/
[ii] https://www.massey.ac.nz/about/colleges-schools-and-institutes/college-of-humanities-and-social-sciences/research-in-the-college-of-humanities-and-social-sciences/psychology-research/new-zealand-health-work-and-retirement-study-hwr/
[iii] https://www.growingup.co.nz/
[iv] The priority groups identified by Manatū Hauora are by no means the only communities who experience inequity in accessing healthcare, nor are they the only groups for whom AI can improve health access. The possibilities for AI to improve equity in health access by making decisions free of human bias, identifying patterns of unequal treatment, and providing new modes of care delivery can benefit all these groups.

aimed to reduced inequity would ideally address intersectional disadvantage. AI potentially enables a broader view of health inequities and tools to address them.

> In its Pae Ora strategies, Manatū Hauora has laid out its vision for an equitable health system, with specific strategies for priority groups who are underserved by the status quo: Māori, Pacific people, people with disabilities, rural people, and women… these categories often intersect and compound disadvantage.

In Aotearoa New Zealand, as elsewhere, most health inequities can be traced to social determinants – "the conditions in which people are born, grow, live, work, and age" [220] – outside the health system, although some of these are specific to our location. Inequities in healthcare often have their root causes in such factors, including the legacy of colonialism, institutionalised racism, and misogyny, which AI cannot address. There is, however, significant scope for AI to identify some of these causes for action to occur outside the health system, and to support the healthcare system to address some of the proximate causes of inequities that are within the healthcare system. Many of our case studies demonstrate that AI tools have potential to support health equity goals if trained on appropriate data sets with goals aligned to desired equity outcomes. Actual provision of appropriate, personalised, and respectful care is long awaited by many groups, and is one of the enticing possibilities that AI offers.

> There is significant scope for AI to … support the healthcare system to address some of the proximate causes of inequities in the healthcare system.

6.5.1. AI can improve diagnosis and treatment to close equity gaps

For decades the health system has systematically underperformed in diagnosing and treating Māori, [215,216,219] Pacific people, [216] and women.[219] Clinicians rely on their training and experience to arrive at a diagnosis on the basis of signs and symptoms and then to prescribe an appropriate course of action. Human fallibility in this process can lead to unequal outcomes. Firstly, when disease presentation differs between groups – as is the case for the most common heart attack symptoms for men compared to women[221] – clinicians may be better at recognising one presentation over another. This problem is compounded when training and education materials neglect presentations common in disadvantaged groups – a situation illustrated well in the field of dermatology, where it is recognised that educational resources tend to lack representative images of pathology in skin of colour. [222-226] Secondly, conditions which are rare in one group may be less rare in another. This will affect a clinician's judgment of how likely a given disease is, [227,228] potentially resulting in minority groups with greater prevalence of diseases that are less common in the majority missing out on appropriate treatments. Assuming AI tools were developed and fine-tuned on diverse data that reflected differences in disease prevalence between groups, such tools may be better than clinicians at flagging rare conditions that disproportionately affect disadvantaged groups.

Another example of how improving diagnostic accuracy with AI could improve equity is in a tool for classifying knee X-rays. In the US, underserved populations have on average higher levels of knee pain and more severe knee osteoarthritis than better-served populations. [229-231] Differences in pain remain even after controlling for radiographically measured osteoarthritis severity, which has been interpreted as evidence that disparities in pain are caused by something external to the knee.

However, this interpretation relies on accepting that disease severity has been objectively obtained by reading X-rays and assessing them against a set of criteria that were developed in white British populations decades ago. To test this assumption, researchers developed an AI tool trained on a diverse US population. [232] The resulting model was able to identify objective features of X-rays that explain a greater share of pain disparities than conventional measures. This study demonstrates the potential of AI to address inequities in health that arise from the patterned distribution of inaccurate diagnoses and treatments, by more accurately identifying patients who could benefit from treatments and in turn addressing disparities attributed to bias in current approaches. [232]

6.5.2. AI can generate insights for fairer uses of resources

AI affords opportunities to address inequitable patterns of service delivery. Our present ability to reduce inequities in allocation is through somewhat crude means such as including ethnicity as part of an algorithm to order surgical waiting lists. [233] AI could increase the sophistication of these kinds of allocation procedures, allowing more precise identification of the people who have the highest need or potential to benefit. Additionally, AI could provide insights into the system's performance on equity that could be acted on in real time, rather than relying on retrospective data. AI would not be limited to considering a handful of pre-specified metrics and could potentially identify inequalities that would have otherwise gone undetected.

> AI could provide insights into the system's performance on equity that could be acted on in real time, rather than relying on retrospective data.

6.5.3. AI enables new ways to deliver care

One of the priorities of the Pae Ora Rural Health Strategy is that health services are available closer to home for rural communities. AI could significantly accelerate this, opening possibilities for digital and remote care. Case study 8, where THEIA enables diabetic retinal screening with a simple app using a specialised camera in a community location such as a pharmacy, for example, would make it much easier for rural people to participate in screening as they do not have to physically attend an appointment in a main centre. Another example is a tool in development in Canada which can measure vital signs remotely in a video call, enhancing the quality of remote service delivery. [132]

Generative AI also offers promise for addressing inequities that arise from language and cultural barriers. Patients could receive written or audio information in the language of their choice. Clinicians could also be alerted to cultural contexts that have implications for the course of treatment they are prescribing.

> Generative AI also offers promise for addressing inequities that arise from language and cultural barriers.

6.5.4. AI doesn't have to make inequities worse

There are many examples of AI amplifying existing social inequalities. However, as these examples highlight, under the right circumstances AI could offer real improvements in health equity in New Zealand.

Data must be fit-for-purpose

A priority for enabling AI in healthcare is to ensure that data sets are fit-for-purpose, both in the training of AI tools and in their application. We need high trust in the data itself, as well as data curation and storage. Poor data has historically been an important contributor to health inequalities overseas and in New Zealand. The *Decades of Disparity* reports in 2003 highlighted that misclassification of ethnicity in mortality data throughout the 1980s and 1990s led to systematic underestimation of the mortality gap between Māori and Pacific people relative to Pākehā. [234] Despite the first report in this series being published more than two decades ago, undercounting of Māori in health data is still a problem with one recent study estimating Māori were undercounted in health and disability sector data by approximately 16%.[235]

A recent report on health equity for Pacific people pointed to significant data challenges for this group, including disputed ownership of primary care data broken down by ethnicity and no requirements around secondary care data despite national policy to promote health equity for Pacific. [236] AI tools trained on data which poorly capture ethnicity will perform less well for some ethnic groups than others overall, while individual patients could be disadvantaged if ethnicity is incorrectly entered into an AI tool used in their care.

AI tools trained on data which poorly capture ethnicity will perform less well for some ethnic groups than others overall, while individual patients could be disadvantaged if ethnicity is incorrectly entered into an AI tool used in their care.

In addition to accurately measuring and reporting ethnicity in data, it will be important to ensure groups who experience inequities in health are well represented in the data used to design AI tools. There are abundant examples of AI across domains performing poorly for people from minority ethnic groups compared to people of European descent, or for women compared to men. The need for bespoke models for each group, as opposed to a general model, will be specific to the health condition of interest. This presents a point of tension with the need for large data sets: communities must feel comfortable to contribute their data to general data sets if the AI tool is to be optimised to their needs. These tensions become acute for small countries and rare health conditions, where the relevant community may be too small in number to furnish a data set of sufficient size to train an AI.

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Another consideration in relation to data for ensuring all people in New Zealand share the benefits of AI in the health system is ensuring that the rich data collected through clinical encounters, administration of public services, official statistics, and research can be effectively brought together as appropriate. There are known challenges around data linkage, including within the IDI. [237] For data held by Manatū Hauora, 86.8% of records were able to be linked to the IDI, with about 1% of those estimated to be false linkages. [238] Linkage failure does not occur at random but follows other axes of inequality; for example, Pacific people have some of the poorest linkage rates within the IDI,

and are additionally underrepresented in the administrative data which comprise the IDI. [239] Moreover, some important data is held by private providers; for example, early childhood data collected by Plunket is not routinely available to researchers or the public. [212] Ironically, while these data issues present challenges to the equitable implementation of AI in our health system, AI may also present an opportunity to address the infrastructural challenges by improving data quality and linkage, enabling the rich data that is already available to be used to improve equity; however, this requires high trust in the systems holding the data.

AI may also present an opportunity to address the infrastructural challenges by improving data quality and linkage, enabling the rich data that is already available to be used to improve equity; however, this requires high trust in the systems holding the data.

Case study 12: Community Acquired Pneumonia and COVID-19 Artificial Intelligence (AI) Predictive Engine (CAPE)

CAPE was co-developed by Changi General Hospital and Synapxe in Singapore as a tool to predict pneumonia using chest X-ray images and electronic medical records data. [240] The tool allows for prioritising and allocation of healthcare resources for critical patients. The risk score generated by CAPE supports doctors to make decisions based on the risk and severity predicted. CAPE is proprietary but is currently being validated in other healthcare settings to make the tool available globally. [241]

Meaningful partnership around the implementation of AI is likely to build trust

Beyond obligations under Te Tiriti (section 6.1), communities are best placed to know what will and will not work in their contexts. Partnership is a practical mechanism to tap into this knowledge to ensure implementation benefits the groups identified in the Pae Ora strategies (Māori, Pacific people, people with disabilities, rural people, and women) as well as other people likely to experience health inequities. Robust processes in this space will also facilitate increased trust and confidence in AI. AI can address inequalities if used purposefully.

Beyond obligations under Te Tiriti, communities are best placed to know what will and will not work in their contexts.

Scholars of health inequalities observes that it is people who are relatively advantaged – by income or wealth, social standing, education, or other factors – who are able to capitalise first on new developments in medical science. [242-245] In the context of new AI technologies in New Zealand, we are already seeing new technologies becoming available in private hospitals and clinics but not in the public sector (case study 14). As AI tools become more important to the practice of medicine, attention is needed to equitable access to these tools through our public providers to avoid exacerbating a two-tier system.

Equity can also be a consideration in strategic decisions about where to pursue AI research and development. Investment in research and implementation could favour AI tools that will benefit the Pae Ora priority groups, or other groups who experience health inequities.

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Case study 13: AI and sign language avatars

One application of AI is the use of transformers, computer vision, and natural language processing to translate spoken language into sign language content. [246,247] Since 2011, researchers have been developing Sign Language Translation and Avatar Technology (SLTAT).

Because language structures are different for sign and spoken languages, there are semantic, physical nuances, social, and cultural contexts for which qualified interpreters and translators must account for. This skill is proving to be a challenge for how machines recognise, translate, and process sign language and then generate effective sign language content. [248] SLTAT is still under development and attempting to address challenges around accuracy, continuous recognition of fast hand, [249] and low quality of generated hands. [246] These challenges are widely known to the extent that the World Federation of the Deaf and the World Association of Sign Language Interpreters issued cautions in 2018 for the use of sign language avatars by public authorities due to problematic word-to-sign translations. [250] Figure 11 demonstrates differences in the quality of generated models.

Aside from the technical challenges faced by SLTAT, there are other issues to consider around the use of digital sign language avatars. These include the use of highly personal recordings of people signing to form AI data sets, deaf culture identity, and model ownership. [251] Given the likelihood of AI deployment across many different domains, maintaining a view of potential biases, discrepancies, and what AI understands as 'norms,' will be crucial. Governing bodies should remain informed of these complexities to ensure that AI tools do not exacerbate injustices that the deaf community already experience.

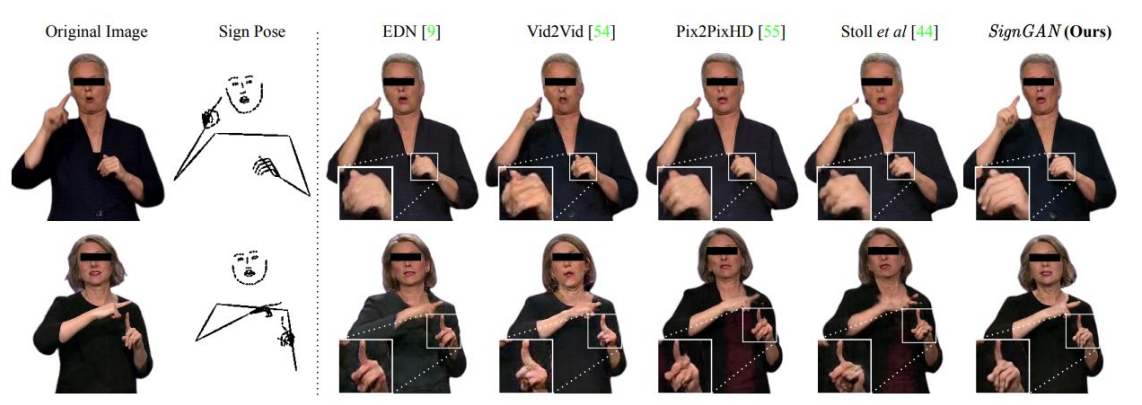

Figure 11: Saunders et al. (2020) comparisons of various models producing photo realistic signs trained on a single signer (top) or multiple signer (bottom) dataset.

Risks of a 'digital divide' in access to healthcare can be mitigated

Some AI health technologies will enable healthcare delivery at a distance. Where these technologies rely on consumers having access to devices and data, there is a risk of exacerbating inequalities. For example, we know that Māori and Pacific people are more likely to experience digital exclusion.[252,253] Enabling infrastructure will be important to ensure we do not inadvertently create new barriers to healthcare access. One innovative solution that could be expanded is Te Whatu Ora's 'Zero Data' initiative which allows free access to health websites from most New Zealand mobile networks without being charged for data use;[254] such a scheme could be adapted for AI-powered health service interfaces. Other enabling infrastructure could include a role for a community member to assist others in using digital services, building trust in its use.

Even without barriers to digital and remote access, some people will prefer to interact with their health providers kanohi ki te kanohi (face to face). Others may prefer to interact with an AI. The health systems might consider how these preferences can be accommodated without resulting in an inferior level of care.

7. WHERE TO FROM HERE?

Prompt: New Zealand's health system supported by AI in surgery. Created using Stable Diffusion on midjourneyai.ai

Key messages

- The impact of AI will depend on more than just the technical capability of the AI tools. An enabling ecosystem is required to ensure that the appropriate AI tools can be developed, fine-tuned and deployed. Appropriate regulatory settings, a strong talent pipeline, and appropriate data are some of the key components to support this
- Strong relationships across public and private sectors, relevant agencies, research institutions, healthcare professionals, and consumer groups will provide useful support to the evolving AI and healthcare landscape
- Aotearoa New Zealand is home to various universities and research institutions that have strong AI capabilities and are open to collaboration. There is potential to capitalise on some of our unique attributes to show leadership in the development and deployment of AI in healthcare by modelling partnership with Māori to develop strong principles for Māori and indigenous data sovereignty, and a focus on equity to improve healthcare outcomes for our priority groups

7.1. An enabling ecosystem

We heard in our engagements that the most significant challenges to fully capturing the benefits of AI technologies are leadership, resourcing, and interoperability. Capturing the benefits of AI in our health system depends not only on the technology but on the wider ecosystem into which AI tools will be incorporated. While a newly developed piece of technology may perform well when tested or evaluated in a specific context, there is the chance that performance will differ when implemented in another health system. [255] Yet, consideration for how AI tools will fit into this workflow is often of secondary importance during the development process. Understanding the wider ecosystem that a new technology is to be deployed in will help to ensure a smooth roll-out, contributing to post-implementation performance and end-user satisfaction. [256]

Capturing the benefits of AI in our health system depends not only on the technology but on the wider ecosystem into which AI tools will be incorporated.

Similarly, the ecosystem can provide enablers or barriers to the adoption of a given AI tool by the health system. We have heard from organisations attempting to deploy or trial AI within the healthcare system that there are several hurdles that make it difficult for New Zealand to be a desirable partner to develop and market AI tools broadly. Navigating the appropriate pathways into the healthcare system is complex. Some stakeholders we engaged described feeling as though there was an indefinite number of hurdles, which cast some uncertainty over their progress once they had finally identified the appropriate teams and agencies to engage. Further, some indicated that access to our national health data is difficult, especially in comparison to their experiences in other jurisdictions. These factors are difficult to measure and complex to resolve. Stakeholders who voiced these frustrations tended to be companies based in New Zealand who felt a strong desire to help 'at home' which may have exacerbated frustrations.

Throughout the report writing process we also encountered groups that expressed positive research and development experiences. For some the benefits of a flexible regulatory system enabled niche

AI research to be commercialised, although slowly. We also heard that targeted investment for AI development in niche healthcare spaces could provide opportunities for New Zealand to compete internationally and could also address some concerns about offshore software dependence. Articulating the enablers and barriers experienced by researchers, developers, and entrepreneurs attempting to deploy AI tools into our national context is necessary to inform governance bodies, decision makers, and policy writers.

Case study 14: Mercy Radiology and Ferrum Health

Mercy Radiology is a Tāmaki Makaurau | Auckland based private medical imaging practice which has introduced several AI tools to support service delivery. Mercy Radiology use multiple tools to support, not replace, clinical decision-making. Dr Remy Lim, Medical Director at Mercy Radiology indicated there is a general sense among staff that the support of AI tools has improved efficiencies in the practice, although no formal assessment has been carried out.

While Mercy is only using three AI tools at present, there is a willingness to try out other tools in future if there is a product that seems suitable to enhance their service provision. The AI tools in use at present support clinicians with fracture identification in X-ray images, removing noise to produce better quality PET images and identification of lung nodules on CT scans. Implementing new AI tools is relatively straightforward and largely depends on the needs of the clinic and the appetite to innovate to support their practice. This was identified as a point of difference to the public healthcare system where additional processes would likely need to be undertaken prior to adopting AI tools.

Mercy uses US-based Ferrum Health to streamline the AI adoption process. CEO and Co-Founder Pelu Tran described how Ferrum addresses the rapid proliferation of clinical AI tools by standardising third-party AI vendors into a single marketplace from which clinicians can choose the appropriate tools. This marketplace is privately deployed into the practice validation and monitoring of Mercy's AI tools.

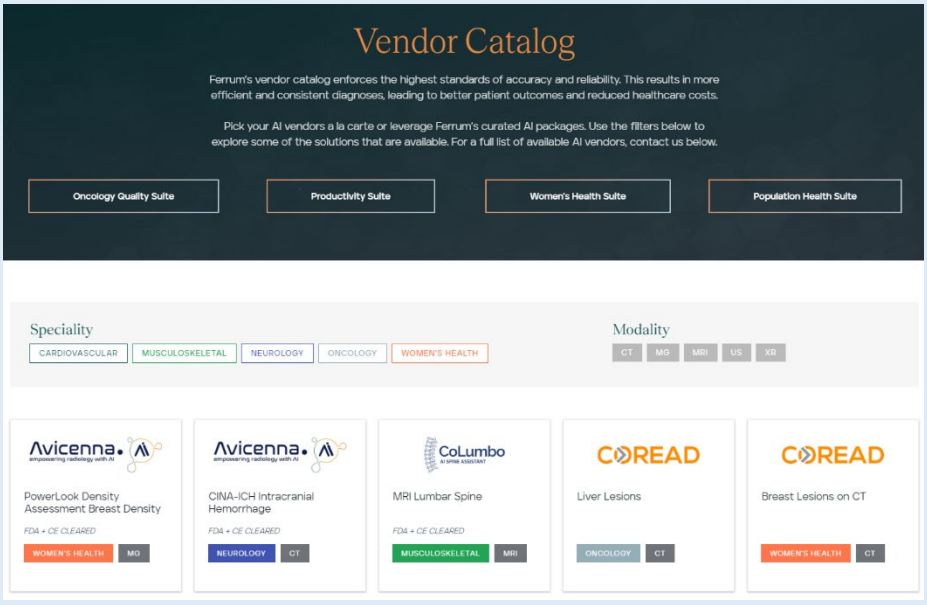

Figure 12: Ferrum Health vendor catalogue (Ferrum Health, 2023)

In preparing this report we spoke to clinicians, health administrators, researchers, AI entrepreneurs, computer and data scientists, and policy makers, among others. We heard about the ways our current systems have both enabled and presented barriers to the process of making safe and effective AI available in New Zealand's health system. Table 6 reflects what they told us (and should be interpreted in this light: some features are verifiable while others are subjective) as well as our own review of the literature and expert consultation in this space. Consideration of how enablers might be capitalised on, and how barriers might be mitigated and/or managed effectively would be useful as AI advancements see a growing number of tools available for potential deployment in our healthcare system. Taking steps to ensure a co-ordinated approach between government agencies, healthcare providers, technology developers, and regulating bodies will help to facilitate a smooth transition to AI supported healthcare delivery. A detailed evaluation of the AI landscape would establish developments that are proven to be safe, effective, and equitable in the current context, but also help plan appropriately to meet future demand.

Targeted investment for AI development in niche healthcare spaces could provide opportunities for New Zealand to compete internationally and could also address concerns about offshore software dependence.

Table 6: Enablers and barriers specific to our New Zealand context

		Enablers	Barriers	Possibilities
Data	Generic	• Good data are crucial to building, using, and evaluating AI in the health system	• Biased, poor quality, or unrepresentative data are challenging to work with and can exacerbate health inequities	• AI enhances data quality, for example, by extracting information from differently structured data sets or by increasing the accuracy of linkage between data sets; this in turn enables more fit-for-purpose AI applications
	NZ specific	• Some of our health data sets are world leading, for example, records from the breast screening programme • The recent health system reform is an opportunity to make data consistent • There is no process for external developers to access data	• Data sets from different sources do not connect • Some parts of the health sector still operate using paper records and notes • There is uneven data quality for different groups	

		Enablers	Barriers	Possibilities
Infrastructure	Generic	• Infrastructure at all levels, from governmental and institutional support [257] to computing capacity and even qualified administrative support in a new technical environment enable the creation and successful deployment of AI in the health sector	• A lack of computing resource and data storage, lack of funding for upfront implementation and maintenance costs in the short term and regular cost of updates of software and hardware in the longer term, and time constraints on staff ability to reorient skill sets limit the ability to adopt and get the most out of AI tools	• AI is alleviating strain on the healthcare system and generating savings by streamlining and automation
	NZ specific	• There is a broad range of institutional expertise across the country including at research institutes (see Annex 5) • Existing connectivity networks for science, clinical translation, and commercialisation (for example, MedTech Research Network) [258]	• Health spending is unlikely to keep pace with technological developments • The project-based nature of research funding makes presents challenges in capitalising on gains. Some sources of funding appear overly siloed. • As a country, we currently have limited computing capacity	
Pathways and processes/institutions	Generic	• Researchers, developers, and entrepreneurs benefit from clarity	• Lack of clarity is a disincentive	• The NZ health system has priority access to the AI tools that will meet the health needs of our people
	NZ specific	• Te Whatu Ora NAIAEAG provides advice on the suitability of a given project for use in the health system	• There is not a clear pathway for developers or entrepreneurs to get their products into the health system, with many targeting international markets like the US rather	

		Enablers	Barriers	Possibilities
			than domestic markets	
Population and culture	Generic	• Trust in AI tools and their governance by both the public and clinicians are facilitated by fit-for-purpose AI, [259] explainability and personalisation[260] of AI tools, strong data privacy and security,[261] and trusting relationships between patients and clinicians[262]	• Mistrust can be caused by a range of factors including fear of surveillance, negative preconceptions, [260] poor public communication, poor/late clinician training, unsafe data-sharing, [257] and high profile data leakage and hacks[263]	• Our population's high AI literacy and positive patient experience bolsters confidence in the health systems use of AI. Our population trusts that risks related to AI are mitigated by good governance. People working in the health sector feel good about their work.
	NZ specific	• Although there is much work to be done, the health system is making progress towards working according to Te Tiriti obligations • Lessons have been learned from COVID-19 vaccination campaigns about messaging to gain public trust • The population has a pragmatic attitude to data use for advancing health	Little is known about clinician's attitudes towards and trust of AI	
Legislative settings	Generic	• Governance frameworks that determine responsibility and liability, [257] and that validate the performance of AI prior to and after deployment, [257] mitigate many of the risks associated with AI	• An overly prescriptive environment would limit the health system's ability to deploy AI tools	• NZ's governance structure ensures AI product safety, quality, and performance, as well as ensuring te Tiriti is honoured and employing a focus on health equity

		Enablers	Barriers	Possibilities
	NZ specific	• Secondary legislation under the TPA will provide clarity about what AI products are regulated as SaMD and relevant product standards • The TPA enables risk-proportionate approval pathways for novel products and embeds a principle of supporting innovation	• The TPA does not regulate all AI used in healthcare. It will apply to certain SaMD that is used for a therapeutic purpose. The TPA regulates SaMD in respect to safety, quality and performance, and ethical dimensions of AI are outside its remit	
Talent and connections	Generic	• Talent and collaboration produce technological innovation	• No single person or team is likely to have full sight of the needs to be filled or opportunities available	• Our local talent pipeline and international collaborations create a thriving health AI sector
	NZ specific	• Our culture of mobility and high levels of immigration provide global connections	• There is no national focal point, such as a Centre of Research Excellence, to foster talent and enable collaboration	

7.2. The last mile

Section 4.2 describes the role of the NAIAEAG who are responsible for reviewing proposals to develop or put into practice any new models of AI in our national health services. New AI technologies that support and enhance the delivery of healthcare are evolving at pace and will continue to do so into the future. However, it is important to consider that development only represents one portion of the journey to achieving better healthcare outcomes.

Founder of the Australian Alliance for Artificial Intelligence in Healthcare (AAAiH), Professor Enrico Coiera describes the development of AI technologies in three stages (figure 13).[189] The challenge of the 'last mile' describes the reality that AI on its own does not do anything. We should consider if and how AI technology connects to real-world processes, and the extent of the associated impact. The 'last mile' can present several challenges including evaluation of real-world impact, calibration to target populations, and quality of fit in a local context. For the operationalisation of AI technology within our healthcare system, it would be beneficial to consider the 'last mile' challenges and mitigating strategies that might support a smoother roll-out.

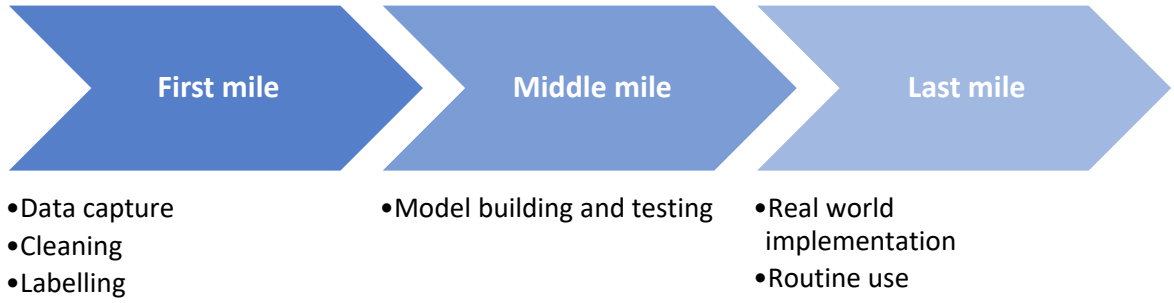

Figure 13: Three stages in the development of AI technologies (figure reproduced from Coiera, 2019).

7.2.1. Post-implementation evaluation

The local context of an organisation is significant factor that shapes post-implementation performance.[256] When a new technology is placed into an environment, the outcomes depend on how well design assumptions match the reality of the environment in which it has been deployed. Requiring ongoing evaluation once an AI technology has been implemented will ensure that 1) ongoing improvement can be facilitated and 2) learnings can be captured and shared with other relevant parties where applicable. For example, where an AI application makes an error, appropriate mechanisms should allow healthcare staff to record and report the relevant information, with feedback sent to regulatory bodies and developers to ensure follow-up and ongoing monitoring if necessary.

There are international examples that we can look to for post-implementation evaluation considerations. For example, the Singapore Ministry of Health include 'Post-Deployment Monitoring' in their *Artificial Intelligence in Healthcare Guidelines.*[118] Guidelines ensure that those implementing the technology maintain ongoing monitoring to ensure continued safety, efficacy, and robustness. Post-deployment monitoring mechanisms also ensure open channels of communication for developers to responds to, and investigate, any adverse events relating to their product. Locally, the Te Whatu Ora evaluation checklist for validation or implementation of a new AI (Annex 2) asks developers to describe mechanisms for ongoing monitoring and audit, enabling regular reflection on product performance and allowing opportunity to upgrade and/or retrain models where necessary. Development of a specific post-implementation review checklist to assess outcomes of newly implemented AI technology is currently underway (see section 4.2).

7.3. Concluding statement

The focus of this report has been on describing the opportunities afforded and challenges faced at the intersection of AI and healthcare in New Zealand. As this report has been produced at pace many of the opportunities and challenges described are brief, we present an overview of various considerations that may be of use for decision-making bodies and policy writers. There are various actions that would support a deeper understanding of the AI tools that would best meet our healthcare needs in Aotearoa New Zealand. We outline some of these pieces of work in our recommendations (see section 3).

ANNEX 1 TERMS OF REFERENCE

Artificial Intelligence – Challenges and Opportunities
Topic 1: healthcare delivery

"The benefits for human society are likely to be immense. AI doctors could provide far better and cheaper healthcare for billions of people, particularly for those who currently receive no healthcare at all. Thanks to learning algorithms and biometric sensors, a poor villager in an undeveloped country might come to enjoy far better healthcare via her smartphone than the richest person in the world gets today from the most advanced urban hospital"

Yuval Harari, 21 Lessons for the 21st Century, 2018

Background

Artificial Intelligence (AI) will have far-reaching and long fore-shadowed impacts on our lives which are starting to be realised at pace. This project will tackle the implications of this rapidly evolving technology with a focus on the opportunities it creates to satisfy unmet needs, in the context of the challenges it poses. We will do this in a series of projects focussing on specific domains, starting with healthcare. AI can assist humans to complete tasks or replace the need for human participation altogether by doing tasks far more efficiently and effectively. The impacts are unlikely to be felt evenly. For example, some have argued that more roles currently undertaken by doctors will be disrupted by AI than those undertaken by nurses.

The list of areas within healthcare that are likely to be enhanced or disrupted by AI include: data collection, use and management; individual access to and analysis of biometric data (for example, from smart watches); imaging and diagnostics; visual and hearing aids; research, teaching and training; all of which raise complex ethical and legal issues. We propose to take an opportunities focus, mindful of the challenges in areas such as the workforce and medical ethics.

The report will consider the use of AI tools to support healthcare delivery in light of our unique Aotearoa New Zealand context. This will include developing an understanding of our current healthcare delivery context and obligations under Te Tiriti o Waitangi.

Proposed Scope

We will focus on the opportunities and challenges at the intersection of artificial intelligence and healthcare delivery, with two objectives:

1. Complete a scan of expertise in New Zealand, to include researchers, businesses, consumers and stakeholders with expertise across disciplines (e.g., computer science, pattern recognition, philosophy, psychology, medical imaging, healthcare innovation, and IT, science and society, data oversight and data sovereignty issues, particularly for Māori, and ethics).
2. Do a deep dive into the opportunities afforded and challenges posed in the healthcare

domain, delivering a short report ahead of the election which includes recommendations for government. Some consideration of how current systems and enablers may need to adapt to maximise the benefits of these new technologies will be included, in consultation with the Manatū Hauora|Ministry of Health (via CSA Dr Ian Town) and with additional input from MBIE. The demarcation between AI-assisted healthcare and 'regular healthcare' is not clear cut and it will be important to understand where existing regulatory frameworks can and can't operate, before complicating the landscape with new regulatory frameworks.

Out of scope

- Macroeconomic implications of AI
- Existential threats and civilisation level impacts of AI
- The intersection of Mātauranga Māori and AI

ANNEX 2 TE WHATU ORA EVALUATION CHECKLIST

Within Te Whatu Ora, NAIAEAG are responsible for reviewing proposals to develop or put into practice any new models of AI in our national health services. [15, 264] Various voices are represented within the advisory group including experts in AI, ethics, clinical, research, Māori health, data, digital, privacy, legal, and innovation. Proposals are considered against the assessment framework that asks developers to speak to various themes and perspectives.

Purpose

Describe the problem the AI is trying to solve, the scale of the problem, inequities, how many people it impacts, the impact for Māori, and current solutions/management. Why is AI appropriate in addressing this problem? Describe the context/settings in which the AI will be used.

Describe the team

Who designed/developed the AI? What are their qualifications/expertise? What is their relationship (if any) with Waitematā DHB?

Describe the engagement of consumers and their perspectives

How have consumers been engaged with in the design/development of the AI? What evidence is there that the use of AI in this context will be acceptable? What are the potential risks and benefits to consumers?

Describe Māori engagement and perspectives

Are any Māori involved in the team or been engaged to date? If not, are there plans to engage with Māori? How will/have Māori perspectives be/been embedded in design/development/testing/implementation e.g. data sovereignty?

Equity and fairness issues and mitigations

Are there likely to be any issues arising from the use of this AI for any specific groups? How will these be mitigated? What is your approach to identifying bias in the AI?

Describe the AI algorithm/model

Describe the methods used, data and features. Has this been/will it be published or made available?

Describe the development process

Describe your development process, including any ethical principles underpinning design and development. Describe training data used and its representativeness.

Describe the use of the AI in practice

How would the use of the AI fit into the clinical workflow? Describe any clinical/operational input. Are there likely to be any concerns or barriers to use by clinicians/other staff? Can these be mitigated? Will training be needed? Is human oversight intended? Where will accountability lie?

Describe the testing and validation process

How will/has the AI been tested and validated? What data has it been tested with? What were the outcomes of any testing/validation already conducted? Was it tested for bias? Does it need to be further validated with data from our health service? What is the availability of the necessary data in our system, if known?

Describe the implementation plan

Is there a change management plan and/or communications and training plan for implementation of the AI in practice?

Describe the monitoring and audit plan

How will you continue to monitor/audit the AI? Outline roles and responsibilities for this. Will the AI be retrained?

Other approvals

Is ethics approval required? Are there likely to be any privacy or security issues that require approvals?

ANNEX 3 PRECISION HEALTH – LONG TERM INSIGHTS BRIEFING SUMMARY

Manatū Hauora released their long-term insights briefing in August 2023. The report on precision health has a particular focus on genomics and artificial intelligence. The report summary is reproduced here.

He whakarāpopoto | Summary

The Public Service Act 2020 requires all public service departments to produce a long-term insights briefing (LTIB). LTIBs are independent of Ministers and aim to look at the medium- and long-term trends, risks and opportunities that may affect Aotearoa New Zealand over the next 10 years and beyond.

This inaugural LTIB focuses on the topic of precision health and has been shaped by the comments and ideas received during our public consultations on the topic itself and the draft briefing. 'Precision health' is an umbrella term for the use of technology and information to develop more precise ways of keeping people healthy. In our briefing, we have focused on two examples of precision health that stakeholders were particularly interested in: genomics and artificial intelligence (AI). These technologies are developing rapidly and present a range of new ways to diagnose, treat and prevent health issues and disease and to use health promotion tools.

Precision health is increasingly being used in both individual and population health interventions internationally. However, its use in Aotearoa New Zealand is currently limited. We have heard from stakeholders who believe widespread use of precision health technologies is inevitable – and in some cases is already here.

There is significant potential for precision health technologies to help us in working towards achieving Pae Ora | healthy futures for all New Zealanders. Specifically, we have heard that there are opportunities to: partner with Māori and other groups from the outset in the design and implementation of new technologies; create more equitable outcomes through targeted interventions and tailored care for individuals and whānau; and make our health system more efficient.

However, we have also heard that the advancement and application of technologies must include ensuring Māori needs and aspirations are being met (for example, protecting taonga such as human tissue, which incorporates DNA, whakapapa, and data). Inconsistent approaches to technology, workforce development and access could exacerbate inequities, and our current regulatory environment may not be well equipped for keeping people and whānau safe. Precision medicines could also unnecessarily displace effective treatments currently in use. For these reasons, it is important to carefully consider and respond to both the risks and opportunities presented by precision health.

Our research and discussions with stakeholders have identified key areas where changes will be needed to realise the opportunities offered by precision health and mitigate risks over the next 10 years and beyond. These are:

- developing systems and processes to enable evidence-based decisions about precision health technologies and infrastructure
- developing a national infrastructure (data and physical) that is sustainable, resilient, and fit for its purpose
- developing effective safeguards and regulations that keep whānau safe and appropriately mitigates risks of emerging technologies
- influencing the design and development of precision health
- building a skilled and diverse workforce that can deliver precision health safely and effectively
- considering specific implications for Māori, both in terms of potential for widening inequities through differential access to new technologies as well as cultural and data sovereignty issues associated with the collection, storage and management of human tissue and genetic material
- rethinking how we can enable individuals and whānau to give informed consent for the use of precision health interventions.

Significantly, feedback also highlighted the need for our Government to provide robust strategic leadership to navigate Aotearoa New Zealand through the vast and complex issues that will arise as we work towards implementing precision health. Important steps are already being taken by universities, Crown Research Institutes and diagnostic labs across the country. However, several respondents in our consultation and engagement process noted that strategic direction setting and support from Government is needed to progress this work further.

This document elevates conversations about precision health in Aotearoa New Zealand, with the insights gathered throughout the LTIB's development providing guidance on what is most important to consider and discuss further.

He mihi | Acknowledgements

We would like to acknowledge all the people and organisations that have submitted feedback and shared their thoughts, aspirations, and experiences to help us develop this final briefing.

This is the start of an important conversation, and we are looking forward to continuing this engagement to ensure we are well placed to explore the possibilities for precision health in the future.

He aha ngā kōrero o tēnei kupu whakamārama? | What does this briefing cover?

There are five sections to this briefing.

The first section describes the purpose of the LTIB, our chosen topic and how we undertook this process.

The second section provides our definition of precision health and explains, how it fits within the reformed health system and how precision health is used in the current health system through two examples – genomics and artificial intelligence (AI).

The third section highlights the most significant benefits and risks associated with precision health, as identified by stakeholders throughout consultation and engagement.

The fourth section sets out areas of the health system that might require changes to realise the benefits and mitigate potential risks in using precision health more widely in Aotearoa New Zealand.

The final section lays out a potential pathway for precision health in Aotearoa New Zealand, including steps and factors to take into account in planning for any implementation of precision health technologies over the next 10 years and beyond.

ANNEX 4 MINISTRY OF HEALTH LEGISLATION – ACTS WITH POSSIBLE AI IMPLICATIONS

The introduction of AI in healthcare settings will have various legislative implications. Our team has carried out an initial assessment to understand, at a glance, what existing pieces of legislation might be impacted by AI in healthcare. A more detailed legislative review will be required moving forward.

Legislation	AI in healthcare implications
Burial and Cremation Act 1964	No
Cancer Registry Act 1993	No
Compensation for Live Organ Donors Act 2016	No
Contraception, Sterilisation and Abortion Act 1977	No
Contraception, Sterilisation, and Abortion (Safe Areas) Amendment Act 2022	No
COVID-19 Public Health Response Act 2020	No
Disabled Persons Community Welfare Act 1975 (Part 2A)	No
End of Life Choice Act 2019	Decision-making
Epidemic Preparedness Act 2006	No
Health Act 1956	Decision-making
Health and Disability Commissioner Act 1994	Code of Consumer Rights – decision-making
Health and Disability Services (Safety) Act 2001	No
Health Benefits (Reciprocity with Australia) Act 1999	No
Health Benefits (Reciprocity with the United Kingdom) Act 1982	No
Health Practitioners Competence Assurance Act 2003	Decision-making
Health Research Council Act 1990	No
Health Sector (Transfers) Act 1993	No

Home and Community Support (Payment for Travel Between Clients) Settlement Act 2016	No
Human Assisted Reproductive Technology Act 2004 (in conjunction with the Ministry of Justice)	Decision-making
Human Tissue Act 2008	Decision-making
Intellectual Disability (Compulsory Care and Rehabilitation) Act 2003	Decision-making - assessments
Medicines Act 1981	Decision-making
Mental Health and Wellbeing Commission Act 2020	No
Mental Health (Compulsory Assessment and Treatment) Act 1992	Decision-making - assessments
Misuse of Drugs Act 1975	Decision-making
Pae Ora (Healthy Futures) Act 2022	Decision-making
Psychoactive Substances Act 2013	Decision-making
Radiation Safety Act 2016	Decision-making
Residential Care and Disability Support Services Act 2018	Decision-making
Smoke-free Environments and Regulated Products Act 1990	No
Substance Addiction (Compulsory Assessment and Treatment) Act 2017	Decision-making - assessments
Support Workers (Pay Equity) Settlements Act 2017.	No
Therapeutic Products Act (2023)	Decision-making

ANNEX 5 AI CAPABILITY SCAN

Our team has crafted a rapid overview of AI research capabilities that sit within our universities and CRIs. Note that this is a preliminary review and a more comprehensive scan, kept up to date, would be a useful resource.

Artificial Intelligence Researchers Association (AIRA)

This is a not-for-profit membership-based group that has members from all eight universities, CRIs, RRIs, and private and industry organisations. Their 2021 white paper *Aotearoa New Zealand Artificial Intelligence: A Strategic Approach* highlights research and expertise within New Zealand and the potential on-shore AI innovations.

Crown Research Institutes

Agency	Use of AI
AgResearch	Is using AI within farm systems, understanding cattle health, food science, and detecting systemic risks.
Geological and Nuclear Science Limited (GNS)	Uses AI across all their databases including decision support models. Particularly for insights, probabilistic forecasts, ground water meta-modelling, geodetic and seismic data, and geospatial data.
Institute of Environmental Science Research (ESR)	AI is used for DNA profile analysis, digital twins research on infectious disease, and environmental changes, agent based modelling for epidemics, and CRISPR based testing for COVID-19.
Landcare	Utilises AI in order to identify and monitor wildlife including invasive species for the use of smart traps. Map urban areas, landslide prediction models, and map soil properties.
National Institute of Water and Atmospheric Research (NIWA)	Is using AI for fisheries monitoring, climate projections, monitoring coastal areas, ecosystem modelling, drought forecasting, and flood risk assessments.
Plant and Food Research (PFR)	Uses AI for genomic research, virtual orchards (digital twins), sensors for volatile organic compounds, computer vision for disease detection, counting, estimation, and crop management.
Scion	AI is used for digital twin forests, predicting tree growth, disease detection, grading seedlings, and aerial imaging to map post Cyclone Gabrielle impacts on forestry.

Universities

Te Whare Wānanga o Ōtākou | University of Otago

Te tari rorohiko atamai, Kaupapa Here Tūmatanui, the Centre for Artificial Intelligence and Public Policy (CAIPP), is the only centre in New Zealand focusing on AI through a public policy lens. The centres social, ethical, and legal capacity also brings in membership from overseas. The Centre has expert capability in multiple disciplines with research on:

- Predictive AI technologies in the criminal justice system
- AI and employment
- Responsible AI for social media governance
- The ethics of social policy uses of predictive risk modelling
- Digital and software engineering systems
- Network modelling
- Conceptual and philosophical frameworks and theories of systems

Te Whare Wānaka o Aoraki | Lincoln University

The Centre for Advanced Computational Solutions (C-fACS) specialises in computational modelling and systems biology. Researchers are focused on:

- AI and machine learning
- Neural networks and soft computing
- Data mining and big data analytics
- Geospatial systems
- Agent-based modelling
- Fuzzy cognitive maps
- Computational and mathematical modelling

Te Whare Wānanga o Waitaha | University of Canterbury

University of Canterbury Artificial Intelligence Research Group specialises in mimicking human intelligence and other biological systems. Their research is applied to machine learning, biologically-inspired computation, artificial life, and meta-heuristic and hyper-heuristic approaches to searching.

AI expertise space across:

- Political science & international relations
- Psychology
- Computer science & software engineering
- Dynamic systems modelling
- Philosophy
- Earth and environment
- Physical and chemical Sciences
- Mechanical Engineering
- Systems biology and bioinformatics

Te Herenga Waka Victoria | University of Wellington

Te Whiri Kawe Centre for Data Science and Artificial Intelligence was launched in 2023 to bring together research collaboration, industry engagement, and commercialisation. Scholarships and internships have also been established to support Māori students and early career researchers. AI is applied to biological sciences, computer graphics and games, economics and finance, linguistics, psychology, software engineering, and computer science. The centre also uses AI for aquaculture, fisheries, the urban environment, and precision farming. Research themes:

- Modelling and statistical learning
- Evolutionary and multi-objective learning
- Deep learning and transfer learning
- Image, text, signal, and language processing
- Scheduling and combinational optimisation
- Interpretable AI and machine learning

The application to their research spans across:

- Primary industry
- Climate change
- Health and biomedical sciences
- Security, energy and high-value manufacturing
- Ethics, society and public policy

A specific AI and society research group has also been newly established to study the impact of AI in industry, economics, law, politics, and culture. The research projects include social media governance and governance of generative AI.

Te Kunenga ki Pūrehuroa | Massey University

There is research at Massey that involves AI within different disciplines. Current projects include:

- Investigating AI and infectious zoonotic diseases linked to climate change
- Cyber security research programme - AI for automating response to threats
- Speech and language (Massey are particularly focusing on processing and translating in Māori, and impaired speech e.g., stroke patients)
- Big data
- Computer vision and image processing in fields like agriculture, horticulture, and marine environments
- Machine learning
- AI and digital business special interest group

Te Whare Wānanga o Waikato | University of Waikato

The University of Waikato is where popular open-source tools such as WEKA, MOA, and Adams were created. Te Ipu o te Mahara, the Artificial Intelligence Institute, was established in 2021 with an international research network and has worked on building strategic influence in the AI sector domestically and internationally. This includes advising on AI governance, operational ethics, and implementation overseas. They support interdisciplinary research with particular interests in machine learning, deep learning, real-time analytics, and open-source software. Waikato's Te Kotahi

Research Institute is also working on Tikanga in technology with research aims including Indigenous data in governance, Indigenous data in systems, and Indigenous data in AI.

Current and recently concluded projects at Te Ipu o te Mahara include:

- Time-Evolving Data Science / Artificial Intelligence for Advanced Open Environmental Science (TAIAO) and Green AI
- User-friendly deep learning
- AI human centric security
- Entrepreneurial universities: real time analytics for big data

The associated groups include:

- Machine learning research group
- The Waikato Robotics, Automation, and Sensing Group (WaiRAS)
- Applied machine learning group
- Cybersecurity researchers of Waikato group
- Massive online AI Lab (MOA Lab)
- Future law technology and society research group

Te Wānanga Aronui o Tāmaki Makau Rau | Auckland University of Technology

AUT's Knowledge Engineering and Discovery Research Institute (KEDRI) has various projects that apply AI.[i] The multidisciplinary team has also developed strong international collaborations contributing to their research. There is currently AI-related research on areas such as:

- Data mining and decision support
- Developing methods of computational intelligence
- Mental/neurological health
- Bioinformatics
- Pattern recognition for radio astronomy and disaster risk
- Neuroinformatics and neurocomputing
- Neuromarketing
- Neuro-tourism
- Neuro-architecture
- Neuro-fashion

Specific projects:

- AI algorithms for prediction of response to a variety of tinnitus therapy
- Computational neuro-genetic modelling for diagnosis and prognosis in mental health
- Intelligent IT to develop novel methods for innovation, interaction, and creativity in complex data modelling and decision support
- Neucube and NeuroGeMS | Te Ara Poutama ō Tāwhaki (case study 10)

Waipapa Taumata Rau | University of Auckland

As a large computer science department, AI research at the University of Auckland spans across multiple research areas and disciplines, and their collaborations extend internationally.

[i] https://kedri.aut.ac.nz/

The School of Computer Science is currently running the following flagship research projects:

- Green computing hub: to foster collaboration and support exchanging ideas and solutions on sustainable computing
- Ethical computing: to address pressing ethical issues in the development and use of technology
- Digital Twin Computer Science Collaboratory (DTCSC): to develop a collaboratory that combines computer science expertise to drive the necessary computing developments for digital twins
- EXTended REality Multi-modal Education and Training (EXTREME): to investigate the use of extended reality (XR) technologies and multi-modal learning for education
- AI and Freshwater Modelling: to protect our freshwater for future generations

The University of Auckland is also home to NAOInstitute and the Centre of Machine Learning for Social Good. NAOInstitute (Natural, Artificial, and Organisation Intelligence Institute) represent the broad field of intelligence research, from biology and psychology, to sociology and business, to artificial intelligence and machine learning. The mission of the Centre of Machine Learning for Social Good is to advance fundamental knowledge in machine learning and data analytics while addressing the most challenging and pressing health, environmental, and societal problems of our time. This is the first centre in Aotearoa focussing on social good by using machine learning in collaboration with domain experts as a catalyst to solve high-impact societal issues. In addition, there are several well-established groups, including:

- Advanced Machine Learning and Data Analytics Research (MARS) Lab is a research group. The lab is developing the next generation of Machine Learning theory, algorithms, and applications. The lab uses Machine learning in real-world applications to make them more sustainable, affordable and resilient
- WICKERlab for Machine Learning: the lab researches machine learning and its application to cheminformatics, bioinformatics, and computational sustainability
- The Strong AI lab: The lab intends to lead in learning-based general AI, focusing on complex problem-solving with Natural Language (NL)

Their expertise and interests include:

- Adaptive problem solving
- Heuristic search or multi-agent systems
- Natural language processing and data streams
- Geospatial data mining
- Bayesian and reinforcement learning
- Ensembles
- Recommender systems
- Matrix factorisation
- Equation discovery
- Fairness in machine learning
- Multi-label classification
- Adversarial learning
- Privacy

Research is applied to bioinformatics, health informatics, computational social science, computational sustainability, and cheminformatics. There is also an established machine learning group with the School of Computer Science that meets regularly and publishes their work.

ANNEX 6 CULTURAL VALUE SYSTEMS AND CULTURAL SAFETY

There is a growing understanding that the pathway to achieving equitable health outcomes requires a level of cultural competency and cultural safety in healthcare settings. [265,266] The need for cultural safety and cultural competency in healthcare service delivery should factor into decision-making around the development and deployment of AI healthcare technology in Aotearoa New Zealand. Within healthcare settings, safety incorporates traditional clinical safety as well as additional factors such as the cultural context of care. [264] Ensuring cultural safety requires that patients are empowered to define quality Within healthcare settings, safety incorporates traditional clinical safety as well as additional factors such as the cultural context of care. [264] Ensuring cultural safety requires that patients are empowered to define quality of care and to be involved in decisions about their care, health outcomes and experiences.

It is widely acknowledged that health and wellbeing is influenced by many factors that are outside of our individual control (i.e., social and environmental factors are also important. [267,268] Across cultures, concepts of health and wellness differ. Taking time to consider the varied understandings of health and wellbeing might support decision makers to determine the appropriate AI tools to introduce to healthcare providers and the appropriate communications to support understanding and facilitate trust across populations. This is directly relevant to any AI tool that is deployed to increase health and wellness.

A 2019 report by the Social Wellbeing Agency describes what service users think of the protection and use of data by the social sector. [269] For Māori communities, a collective approach to wellbeing was highlighted, enabling a focus on the many aspects that make an individual and their whānau well. [269] For Māori communities, a collective approach to wellbeing was highlighted, enabling a focus on the many aspects that make an individual and their whānau well. That health and wellbeing is a holistic and relational concept for Māori necessitates models of healthcare delivery that build trusted relationships and take a relationship-based approach, incorporating the wider whānau. [270]

For Pacific peoples, understandings of health are holistic, taking into consideration physical, mental, spiritual, social, and economic wellbeing of the community. [216] Despite the increasing diversity, several cultural values are consistent across Pacific groups. [236] The appropriate respect and consideration for these values as AI is implemented into our healthcare delivery services will form a strong foundation for a thriving Pacific population in Aotearoa.

Asian and other ethnic populations account for around 18% of our population in Aotearoa New Zealand (as at Census 2018) and includes over 40 sub-ethnicities. Our Asian population is diverse and has not been systematically reported on as an ethnic category; however, some progress has been made over the years. [271] Lack of data and capability to meet language and cultural needs for Asian peoples when accessing healthcare services are known areas for action and where AI can support successful outcomes.

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Prompt: Surrealist painting of an emergency department in New Zealand with robots. Created using Stable Diffusion on huggingface.co

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