How can we overcome bias in healthtech?

The G Word Transcript

**Lois:** Hello, and welcome to the G word. Today we will be discussing the complex landscape of healthtech bias with our incredible panel of experts. Thank you so much for joining us.

My name is Lois, and I'm legal counsel here at Genomics England, and I'm your host today. It is my absolute pleasure to introduce our three guests today.

Sarah Kerruish, Chief Strategy Officer at Kheiron Medical, a UK-based medical technology company leveraging artificial intelligence to improve breast cancer detection and diagnosis.

Hélène Guillaume, founder and CEO of Wild.AI, an app which is designed to help women train, fuel and recover based on their physiology, to help reach peak performance levels.

Dr Emilia Molimpakis, co-founder and CEO of thymia an AI model, which uses voice movement and behavioural data to offer clinical insights into mental health and wellbeing.

Our guests today will share insights on the challenges surrounding bias in healthtech, from algorithmic biases to data disparities. We'll explore the pressing issues and delve into potential solutions and discuss a way towards a more inclusive and equitable healthtech future.

So, I will be starting off with some questions around genomics, AI and data. The first question is, how can incorporating additional modalities and biomarkers, such as genomic data, into AI models help bias in healthtech? And why is this important for promoting equitable healthcare outcomes, and we'll start with Emilia on that one, if that's okay.

**Emilia:** I think that's a really interesting and also very exciting question. I'll approach it from more of a mental health perspective since that is my specialty, and I would love to hear others' opinion on the physical side. I think particularly with mental health, what has been found for decades really is that the current gold standard of assessment is actually incredibly biased.

There is a massive gender bias. For instance, women are much more frequently diagnosed as having depression than men. Also, there are age and cultural biases there, and that has to do with the way in which the assessments themselves are kind of not as sensitive to these differences as they should be in these cases – adding in data from other elements actually could help bring more objectivity into what is an incredibly subjective area.

But in general, as probably Sarah and Ellen would agree, the more data you have on stuff, the better, the better overall the outcome is going to be as well. Most recently, we actually published a paper showing that if, say, just looking at mental health and depression, if you start with looking at biomarkers through voice, and then you add in biomarkers you can pick up from videos - so, looking at things like facial expressions, eye gaze patterns, upper body movements - and then you add on top of that anything else you can pick up from wearable devices or behavioural elements in how people interact with their phones, each modality you add increases the accuracy relatively of your model by 12 to 15%.

So, that is a massive boost in and of itself. There's a really strong reason to do that. But in general, I think the more handles you have, the more likely you can triangulate what the actual problem the patient is experiencing is. So, it's really important to add in as much as you can. At least that's kind of our approach.

**Lois:** That's really interesting. Thank you so much for that. Sarah and Hélène, I'm not sure if you had anything to add in terms of, you know, multimodal data, different types of data fitting into a model.

**Sarah:** Yeah, I mean I think it's going to certainly transform our understanding of cancer, for example. So that's where I'm focused on, building AI models that detect cancer earlier with an initial focus on breast cancer. We've started the development of our models with one principle, which is we start from a place of inclusion, and that means making sure that we have data that's representative of different ethnic populations, different genetic populations, and we bring in that data, that imaging data, that genomic data, to give us a much more robust indication of what's actually happening, how we pick up that cancer, what that cancer means, what the prognosis for that cancer is, and the potential treatment for that cancer.

So, I think multimodal is the future, but we have a very special responsibility to be inclusive - to make sure that we are completely rigorous and robust in making sure that women and people from ethnic minorities are represented from the beginning and not as an afterthought.

**Lois:** How is prevention linked to precision medicine, and in what ways are healthtech companies incorporating diverse data sources? You just alluded to that, Sarah, and using AI to advance precision medicine. Emilia, if you wouldn't mind starting us off there, that'd be great.

**Emilia:** Sure. I think kind of building on the previous question around accuracy improvement through multiple modalities or including more data points, the more accurate you are and the more data you have, essentially the more precise your outputs are going to be.

I think there is a - maybe a misconception that that only applies when there is an advanced illness at play, or when you are just looking at treating someone who is at secondary or tertiary care stage, but actually that's really not true. Precision medicine can apply very easily and nicely, even at the prevention stage. Prevention is becoming more and more recognised as the area people need to focus on in order to stop both the actual progression of the illness, but also all the associated issues around that, from costs to actually the patients themselves having to deal with more and more as they go on.

So, if you can actually bring precision medicine to prevention, then obviously that's really, really helpful. thymia, actually we started very much focused on secondary care. We started working with a psychiatrist, neuropsychologist, in the very bad stages of major depressive disorder and people who border on tertiary care.

Most recently we've started trying out using our technology, which focuses on monitoring symptoms accurately and objectively. We've started looking at offering that into the pre-primary care stage - or preclinical stage, if you want to call it - and actually the results have been really incredible, and people are really willing to start incorporating that kind of precision medicine even at the prevention stage. I think the more we use it, the more we'll see that actually this is, as Sarah was saying – the future is multimodal. The future is also, I think, prevention. So, I think it's definitely very, very applicable.

**Lois:** Amazing. Thank you for that. Interesting what you said about that. Interesting what you said about the intersection between precision and preventative medicine. You want to have both working together, I guess it's about tailoring to an individual and kind of looking at their phenotype environment, lifestyle, genetics, and bringing all of that together. I'm not sure if we had any further comments on that, Sarah.

**Sarah:** Just that we can get access to some of that information ourselves today. Just those basic genetic tests, you know, our sensitivity to caffeine, our likelihood of developing certain diseases. I think that in the future, medicine, it's trending towards functional medicine, which is understanding the basic dynamics of disease and the precursors of disease, and by doing much more tailored testing and different kinds of testing, then we can develop that sort of whole life portrait of somebody and perhaps understand where they may have vulnerabilities, based on their history and their genetics and their predispositions and their environment.

So, all kinds of things that we can take into account. I think that is the future. It'll be much less about treating symptoms and much more about really understanding those fundamental dynamics of disease and what those early indications are and how we can head that off. I mean, diabetes is a good example of that. When people are trending towards diabetes, intervening early and making sure that you make those adjustments to diet.

**Lois:** Hélène, I'm not sure if you had further comments to add there?

**Hélène**: At Wild.AI we really look at how to understand symptoms early so that you don't have to have negative symptoms. It's very much on the preventative side and the personalised approach to your own body. So, how can you understand your own body, your own symptoms, and what is happening? And so, just quickly on how it works for us as a company, we take data from wearables and manually input, aggregate these two together, which gives us a readiness score, and based on the score, provide the recommendations that adapt to you on exercise, nutrition, supplements, and recovery.

**Lois:** So, do you have any concerns about the use of AI in healthcare and how can we ensure that AI is used in a fair and unbiased manner? Emilia, we can start with you.

**Emilia:** Yeah, sure. I think this is probably one of the most timely questions. I think there is this sense now, with Chat GPT and all the new AI advances, we keep hearing about that there is this sense that AI is amazing - it's this fantastic future for everything including healthcare. But while I agree that there is a lot of room for excitement and we should be excited at the same time, AI isn't just naturally the cure for everything. It's not panacea, AI, despite the name. I think people seem to forget that AI is not inherently intelligent. It doesn't itself know that it is making the right decisions or the ethical decisions, or anything like that.

All it knows or understands is how to build patterns that it learns from the data you feed into it. That's actually the real issue, I think, is that a lot of the time people aren't aware enough that the data they're feeding into their models may actually be biased and what the model then ends up doing is it just propagates that bias. It's not doing it, you know, malevolently or anything like that, it's just learning based on what you give it. So, it's like garbage in, garbage out kind of thing. So, you need to be very, very careful, like Sarah was saying, about inclusivity and making sure that you are sampling what you're training - your model is incredibly representative of the actual population you want to represent. That's one way of doing it. But also, when you're actually done with the model and you've built it, you need to make sure that you are testing it and segmenting your results across those different areas that may be biased.

So, quite commonly found, say in mental health, is gender. I'm sure in most healthcare applications when you're done with your model, you should be segmenting by gender to make sure that your results are actually still on point for those different segments. This is just a simple example, but you should be checking for bias. I think that's one big thing.

The other thing that's really important, particularly when you're going into these new areas like mental health, AI is very new, I think it's tempting to completely exclude the doctor from the equation and say, oh, we can do this better than you. I think we should really be very, very careful when we're doing that. Like, ethically, I still think that we should always have a doctor in the loop, essentially always being there, making the final decision, the final call, whether that's for a diagnosis for treatment, it’s really important that we still include that human in the loop because they can pick up if there's something like really fundamentally wrong.

And also I think it's very important to have that human in the loop to check for biases, but also build handles into your models, like ethical AI handles essentially, that you can go back and check, is the output what I expect it to be? if not, then you have like this warning sign somewhere that flags it up and you can go and you can correct for it.

So, just because you have a model that kind of, or not kind of, but works really well, it doesn't mean it's perfect. You should continue to improve it and correct for it.

Finally, I think though, the other massive thing that Chat GPT has also brought up like really, really profoundly is you need to tell the people that you're working with, or the user, that actually they're interacting with an AI. This is not necessarily a human they're interacting with, say, and that's something that's very important both to recognise for the end user, but also it's very important for the consent also that they're giving in the AI or the other person on the other side processing their data. I think that's so important.

**Sarah:** The other thing I would add is teaching people how to evaluate AI models. It's one thing to be able to develop an AI model in a lab that can work on a very limited data set, but what does that actually mean - especially in healthcare when it's in the real world, which is very messy. So, I think making sure that the evaluations that are done with those models are representative of that population, at scale.

I mean, we find quite often that people dock to their data sets. They're technically representative in that they have the right percentage of negatives and positives, but they're not actually from a sample of that population. They're constructed. So, there are all kinds of minefields. As you approach this and as you decide, well, which AI should I use and how do I use it, and does it suit my purpose? And I think there's a whole new level of literacy that we need to bring into the landscape in terms of, how do you make those decisions? What are the things you look for? How do you know that this works better than that? It's, you know, even I've read a lot about the space and even now I read papers and it's just mind bending. You know, in terms of the statistical analysis, or the plan, or the trying to understand the data in any meaningful way to understand potential biases for that technology. So, I think that a new level of literacy and ethical thinking is required, and it's incumbent upon us to take that very, very seriously.

**Lois:** I think that's a really interesting point, Sarah, about evaluation. I was reading that, in many AI studies, particularly machine learning, there's no kind of reporting of the demographic breakdown of the training data. So, you know, lack of reporting, making it really difficult to do that evaluation, evaluating the bias and the fairness of the AI solution and also its applicability across different populations. Do you think there should be more standards in place? Should there be more consistency across the board in terms of these evaluations? I know there's a minimum information for medical AI reporting, but whether or not that's broadly adopted, I don't know.

**Emilia:** Yes. One of the challenges we have is that there are many bodies and many guidelines. I think that's challenging to navigate, but I'm sure there will become a consensus that is reached. I mean, there are some things now that I think everybody agrees on, but I think we'll get to those principles, but it's something we should all be very focused on.

**Lois:** I guess the danger is that there's also the opportunity for bias at a few different stages of model development and deployment. So, it has to kind of be monitored, end to end, and then ensuring that it's deployed in a fair and unbiased way and the intended use of the model is what's actually happening out there in the real world.

**Sarah:** Absolutely, and very small things can change the performance of a model. In our case, a software update to the actual mammography machine that captures the image for the mammogram. You know, small changes in the way those images are processed can make a difference in terms of the performance in our case, AI technology.

So, I think that’s also having those alerts, knowing where there's a shift in performance, knowing what can cause those shifts in performance. It's going to be very interesting, the next few years, as we work how to robustly generalise and monitor AI in healthcare. But I think, fundamentally, it comes down to very careful deployments, you know, making sure that you do evaluations at sites, even if you have a technology that you think generalises in the same way that, you know, when you introduce a new blood testing and machine - actually don’t know the name of it - but in a hospital they always do that calibration test. So, these deployment methodologies are key to making sure that we can actually introduce healthcare AI solutions safely and they are as important, if not, well, they're as important as sort of large scale retrospective evaluations.

**Lois:** Really interesting. Thank you. I guess some of that comes down to training people on the ground on how to use them, but also you know when things go wrong.

**Emilia:** Yeah. Training is important. Monitoring is important. One of the beautiful things about AI is you can often evaluate it in shadow mode without actually affecting clinical care, but that's a really safe way to make sure that a technology and AI technology is working at a site.

**Lois:** Do you think it's necessary for data to be open?

**Hélène**: What typically happens is that the human subjects that the data is collected from haven't always agreed or consented to that data being made public or to that data being transferred from the first place to the second place, the third place, whatever that is. Sometimes they haven't even consented to you gathering their data at all.

So, I think there is a balance as long as the end users, or the patients, or the people who we are gathering data from, are consenting for that data to be made public, or for other companies, other research groups to use that data, then I think that's fantastic.

**Emilia:** The other thing I would say is communication. I think there are amazing opportunities for advancing medical science and through AI and many other ways by opening up data sources, by connecting data sources. The UK is in an amazing position in that regard, Genomics England, NHS Data, just an incredible place to develop new insights and technologies and advancements in medical science.

But I think we haven't done a good job of communicating with the public. I think if you actually sat down and had conversations with most people and you explained how data is likely to be used and why it's important, then I think we would get much further in terms of being able to make important data sets available.

We've had a few major setbacks here in the UK, particularly regarding attempts to do this that have failed, and I don't think they failed because people don't want to contribute to science. I think they've failed because we haven't found the right ways to communicate about it and perhaps to put the right safety measures in place.

I think it's a huge opportunity, and I think it's something to continue to work towards, but with that thoughtful, careful approach, and with better communication with the public.

**Lois:** Really interesting. Thank you. We are going to pick up on some of the themes we've already addressed. So, one of them being bias, and Sarah, this was a question we had for you initially. Why do you think it's important to address bias in healthtech? We've touched on some of these themes already, but such as the underrepresentation of women in healthtech data, and what impact can this bias have on patients and healthcare outcomes? We'd be grateful for your thoughts on that.

**Sarah:** Well, it's devastating the impact that it can have, whether it's understanding disease, treating disease, making sure that we are addressing the right people, getting them the right help.

It’s so fundamental and it's such a fundamental inequity. I mean, we saw all the horrendous statistics during Covid about how Covid affected certain populations. I was just reading another statistic about women giving birth and that black women were much more likely to have a bad outcome in a birth scenario, even in developed countries.

I just think it's the absolute route of equality and something that we need to pay much more attention to. I think it's starting to become part of a wider conversation. I think people are starting to understand how important it is. I just think it's really fundamental. In breast cancer screening, for example it's really important that we make sure we have data representative from many different ethnic groups because breast tissue is different. So, Asian women have much denser breast tissue, much more difficult to read from a mammogram point of view. And that's where, you know, that's where we need to make sure that we work with multiple different populations all over the world. It's why we have a relationship, an academic partnership with Emory, for example, which has a large African American population, or UCSF, which has a large Asian population.

We're just starting to do the granular assessment, because in the UK certain sites collect ethnic information, so we can actually go and look and see how near our technology is performing against different groups specifically, not generally. But yes, I don't think we can take it seriously enough.

Historically we've done a horrible job. I mean, women weren't even included in clinical trials until, what was it, 1980 something.

**Lois:** It was ridiculous, it became federal law in 1993 in the US. It's shockingly late.

**Sarah:** Unbelievable, it’s crazy, isn't it? Also, certain ethnic minorities have been, their data has been badly misused in some horrendous cases that are probably familiar to everyone. So, we just need to do a much better job of making it a priority.

**Hélène:** I think on the way you were saying, using mode data and AI and how we can optimise all these things, there's one thing that we are doing with Wild.AI which is interesting, is looking at federated learning. So, how can we not share data sets but share learnings with other companies that are doing research, which means that we can understand. So, we have specifically dataset on women. Another company for instance has data sets on human on longevity. How can we understand cross correlations between data on women longevity data and contribute towards that? I think one of the conversations with Genomics England, you have a huge amount of data sets, and how can we collaborate better as companies in the UK to really advance research because each of us are in silos?

We have a lot of data sets, but how can we obviously respect the GDPR global data privacy regulation, not share the data, but the learnings. That's one point on better use of AI because we can use a lot of algorithms that optimise learnings if we have more data sets.

And then, back on the data that is biased data sets, we saw in our company an interesting anecdote, we were talking about data creation and for the algorithm AI to be valuable, we need to understand that the data input is diverse or interesting. And we had this conversation on what data to track as a company. And we were two women to men, and we were saying, we should try, we should track sex drive because it's an interesting data point. And the men were saying, well, it never changes so we shouldn't track it, so, it's a non-data, and as women were saying no, it changes all the time. So, it's actually really interesting.

So, if we look at a team of engineers who don't understand diversity, they can actually not have this creation level of data, the creativity to have more data inputs. Today we can still today have a lot of issues with the algorithm because often there isn't the diversity and data creation level for example using female data sets. All the diversity of women using contraceptive or in menopause are completely different ethnicities of people, etc. So, when we have, or that example in our team, we had trackers who look at the colour of blood for your skin, but it doesn't work really well for darker skins. So, again these devices wouldn't be relevant for people with dark skin. So, yes, diversity of data creation is important.

**Lois:** Emilia, did you have anything to pick up on the previous question?

**Emilia:** Well, I was going to add on the gender bias, or lack of representation of gender, you mentioned questions around, you know, pharmacologically, how women respond to different drugs, or going in depth and just the differences - physiological, biological differences - between men and women. I wanted to highlight, in mental health, you have even more kind of crude examples of how the assessments or the way that we look at these things are actually not equal between men and women. I can just give you a couple of examples.

When someone is trying to assess as a psychiatrist or as a clinician, a person for mental health issues, they will ask them, how frequently do you cry? Or what is your sex drive like, which is what **Hélène** talked about as well, or have you thought about leaving your family, or these different questions. Just from those questions alone, you can probably guess how differently men and women actually respond. There is a massive difference between, you know, women are much more likely to admit to crying or to not admit to wanting to leave their family, whereas men respond very, very differently. There is this kind of an interaction of culture and gender there, but it's very fundamental and yet this is still the way that you assess mental health despite this massive issue and actually that is represented in the data. Women, as I said earlier, are much more likely to be diagnosed as having depression or having worse symptoms of depression because of these precise differences, essentially.

**Lois:** So, how do we get around that? Is that just the development of, you know, questions and metrics that better suit how mental health presents in women? How do we go about addressing that?

**Emilia:** I may be incredibly biased here, but my opinion would be that you need more objective measures, not just questions. So, combining genetics, combining analysis of voice, analysis of behaviour, all of those things together, that's probably the only way that you can measure something like the human brain without talking to the human brain, if you see what I mean.

There is a fundamental issue in mental health. You are asking someone a question and the thing that they're using to answer the question is the thing that you're asking about, which is very kind of circular and problematic in many ways, gender being one of them. But yeah, I would say trying to get as many different types of data together as possible to get the true story.

**Lois:** That's great. Thank you. And that leads really nicely to our next question. So, what are some strategies that healthtech companies can use to reduce bias in their products and services? We've already had some great examples of this, but if anyone else would like to add anything, please do jump in.

**Sarah:** One of the interesting things about AI is that we don't have necessarily the same issue of needing to recruit patients as you would in a clinical trial for a drug, for example. And so, in some ways it's easier, as long as you're diligent and thoughtful, to get access to the right information that could inform your models in a meaningful way. So that's what I was referring to earlier when I said we made sure to work with academic centres all over the world with very different populations to make sure that we got the right data from the women that we aim to serve, you know? We say that we want Mia to work for every woman everywhere.

It will take us years, but we've made really meaningful strides and we have really good indications at Emory, for example, that Mia is working equally well for African-American women. So, I think actually we have a really interesting opportunity and why that's meaningful is because certainly there are populations who are much less likely to engage in clinical trials, and that's been a big source of issues. For example, in cancer trials in America, getting the African-American population, which has a high prevalence of cancer, engaged in trials is more difficult. Native Americans have a long history of abuse. Quite frankly, in terms of people misusing their data or misappropriating their data when they have participated in clinical trials.

So, I think there's an interesting opportunity to redress some of the imbalance as long as we are thoughtful about which data sets need to be represented in our models.

**Lois:** I guess it's about building that trust and having that transparency in terms of how data is used, and then hopefully we can progress over time towards a more balanced view of the drug or the therapeutic and how it should be used.

So, the final question of this section, and we've touched on this slightly, but the idea that some conditions have unique, specific presentations in women. So, for example, stroke, diabetes. Are we moving towards better recognition of these presentations, I guess with the more diverse data that we have, with multimodal data? What do you see happening with this specific side of things? Sarah, if you wouldn't mind starting.

**Sarah:** Yes, the opportunity is there whether we take advantage of that opportunity. I think that's the question. I think it still horrifies me that so many conditions are still, you know, even things as basic as a heart attack, that women still don't know the basic symptoms of a heart attack. What's propagated are the symptoms that men experience, that's still true today. So, I think we have a long way to go, but definitely that's the opportunity to make sure that we understand much better a woman's experience as it relates to her body and disease, and then making sure that we develop technology and algorithms that address those differences.

I would also say focusing on things where I just think, women's disease, diseases specific to women, are so still so underrepresented, under misunderstood like endometriosis, for example. it's horrifying the lack of funding that's going into those, understanding those diseases, menopause, you know, so there is definitely an opportunity for AI to help us understand women's health conditions better and try and bridge that divide, that information divide as well as the treatment divide.

**Lois:** Thank you for that. Hélène, I know so much of what you do is relevant to this. Did you have anything to add there?

**Hélène**: I think it's insulting that nothing has been done, as Sarah, you were mentioning endometriosis, 10% of women have it. PCOS, 10% of women have it. Menopause, every single woman on the planet will have it. Yet we have so little knowledge, and with the computing power today that exists, the data gathering power that exists today, the fact that we're still at the nascent phase of understanding a bit more about these big life stages that so many women will go through is insulting.

The good news is some companies are changing and doing things on that. We're one of them, helping women understand the power of having menstrual cycles, understanding the symptoms they might go through if they are perimenopause, **w**e cover 149 contraceptives. They're all different if you use a copper IUD, they are different to the mini pill or hormonal IUD.

So, it’s crazy that there isn't a lot that has been done, but we are seeing a few companies emerging in the sector and trying to flip the conversation. On the bright side is that it's such an amazing opportunity for the companies like ours because it means, you know, if you're in research, having a field where so many people who want to be researched on. Whenever we send a call for research, the las we did we had 2,000 applicants in two days to do continued glucose monitoring research with us because women really crave being analysed and understood better.

To go back to the point, the bright side is we have so many women interested in being researched, really craving new solutions. They're unhappy with the current solutions. So, the good thing is that anyone who is going into this field today, actually will possibly have a very successful business because there are so many women that are underserved.

**Lois:** Just wanted to thank all three of you for taking part today and for your time. We really, really appreciate it. If there are no further comments, then we'll leave it there, but thank you so much for being here. We really, really do appreciate it. Thank you so much indeed.

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