WorldPop

Age-Structured Mapping preprint - audio summary

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Transcript

Speaker 1: Welcome to the Deep Dive. We know there's just so much information flying around. Our goal here is simple. Cut through that noise and give you a real shortcut to being well informed. We break things down; you get the insights now before we properly dive in.

Just a quick but important note. We aren't real people. We are AI derived from source material that was uploaded by WorldPop and this audio it's been edited, checked and carefully validated by the experts at WorldPop.

OK. So today we're getting into a really interesting preprint journal article. It's led by WorldPop researcher and associate professor Doctor Edson Utazi. The title is *An Age Structured Spatially Varying Coefficient Model for High Resolution Mapping of Vaccination Coverage*. Important stuff.

Speaker 2: Oh, absolutely vital stuff, because, you know, having reliable, really granular vaccination coverage estimates, that's just fundamental for any effective public health action. Think about it. These big national averages, they can easily hide really critical patterns. Immunity gaps that you just don't see otherwise.

Speaker 1: Right. So, if you don't know exactly where the problems are or who is being missed.

Speaker 2: Your interventions just won't hit the target. They won't be effective.

Speaker 1: OK, so let's unpack that a bit. These hidden patterns you mentioned. What's the core problem with relying on that older, maybe less detailed data.

Speaker 2: Well, the main issue this research tackles is that traditional data often gives you just one big number. Say 80% coverage for the whole country. But that number completely masks huge differences. Maybe it's 95% in the cities, but you know way lower, maybe 50% in some rural areas. And crucially, it also hides differences between age groups. So, you might think, oh, 80%, that's pretty good, but you're missing serious gaps in specific places or for specific kids.

Speaker 1: Which makes targeted strategies almost impossible, right?

Speaker 2: Exactly. You can't target effectively if you don't know where the target is.

Speaker 1: OK, so that brings us to Dr Utazi's work. What's the innovation here? How does this new model help reveal those hidden patterns?

Speaker 2: So, what's really fascinating and quite innovative, is this spatially varying coefficient model they developed. What makes it so, well, innovative?

Speaker 1: What's really fascinating and quite novel here is how it uses those spatially varying coefficients. See they weren't used in the typical way to model, say, the relationship between coverage and things like distance to clinics or poverty levels.

Speaker 2: OK, so not for the usual covariates.

Speaker 1: Exactly. Instead, the model uses them specifically to account for spatial non-stationarity. That's how things change across space, and the differences in coverage between different age groups.

Speaker 2: Differences between age groups changing across space? Can you break that down a bit?

Speaker 1: Sure, think about the gap in coverage between, say, a nine month old and a 23 month old. This model doesn't assume that gap is the same everywhere. It allows that difference that age specific gap to vary from one neighbourhood to the next or one district to another. It maps the variation in the age gap itself.

Speaker 2: That's subtle. But it sounds really important. It's getting at where specific age groups might be falling further behind compared to others.

Speaker 1: Precisely, it gives you this much finer lens on potential delays or access issues for specific age windows, location by location.

Speaker 2: And I gather the models pretty flexible too. It doesn't just look at one specific age.

Speaker 1: That's another strength. It's applicable for estimating coverage right down to a single age point, like exactly 9 months old, if the data supports it. But it can also handle broader birth cohorts. You know, looking at children aged 9 to 11 months or maybe 12 to 23 months together. That flexibility is really useful depending on the programme needs.

Speaker 2: And this lets them create these incredibly detailed high resolution maps, maps that show the variations the heterogeneities not just by place, but also specifically by age group.

Speaker 1: Ah, so with multi layered geography and age?

Speaker 2: Precisely, it uses individual level survey data to really pinpoint where the immunity gaps are and importantly for whom.

Speaker 1: That level of detail sounds like a game changer. So, they applied this model. Where did they test it out and what did they find?

Speaker 2: They applied it to measles vaccination coverage, specifically the first dose. MCV1 for young children aged 9 to 35 months in Cote d'Ivoire. And here's where it gets really interesting. They found something quite surprising. Children who are a bit older in the 12 to 23 month and 24 to 35 month age brackets. They had roughly twice the odds of being vaccinated compared to the younger infants, those aged just 9 to 11 months.

Speaker 1: Wow, twice the odds. So, they were twice as likely to have gotten the shot.

Speaker 2: That's right. Which points to a pretty significant delay in getting that first measle shot during the critical first year of life for many children.

Speaker 1: That really highlights the timing aspect, not just whether they get it eventually. What about the where? Did the map show specific hot spots or cold spots?

Speaker 2: Yes, absolutely. If we connect this back to the bigger picture, the maps clearly showed lower coverage for those youngest infants - the 9 to 11 month olds. And this lower coverage was particularly concentrated in the western and northern districts of the country. But then you had other areas like Lacs, Vallée du Bandama, and the capital region, Yamoussoukro showing consistently higher coverage across all the age groups studied.

Speaker 1: And did the model pick up on why? What factors seem to be driving these differences?

Speaker 2: It did. It identified several key factors influencing the odds of vaccination. Interestingly, living in an urban area was actually associated with lower odds.

Speaker 1: Oh, that's counterintuitive. You'd think access would be better in cities.

Speaker 2: You would, wouldn't you? It suggests there are more complex dynamics at play, maybe related to population density, mobility or even access challenges specific to urban slums, perhaps. We need more granular data like this to understand it.

Other factors included distance to conflict zones, how long it takes to walk to the nearest health facility, the mother's level of education. And get this, health card ownership. Possessing a health card was linked to a six-fold increase in vaccination odds.

Speaker 1: Six-fold that's enormous! Really underscores the importance of just having that basic documentation and connection to the health system.

Speaker 2: Absolutely. And access to media also played a role.

Speaker 1: So, bringing it all together, what does this mean practically for you know, the people working on the ground in public health?

Speaker 2: Well, that's the crucial point. These detailed maps aren't just academic exercises. They provide truly actionable insights. They allow for the design of really targeted interventions.

Speaker 1: So instead of a blanket campaign.

Speaker 2: Exactly. And so, instead of saying get vaccinated everywhere, a health official can look at these maps and say, "OK, we need to focus our resources right here in this district and specifically on reaching the 9 to 11 month olds". They can see where catch up activities are most needed or where access to services needs improving for specific age groups. It's a shift from well kind of broad guesswork based on averages...

Speaker 1: ...to precise data-driven, impactful strategies.

Speaker 2: Precisely.

Speaker 1: So, this Deep Dive really shows how this kind of modelling Dr Utazi's work offers a powerful tool. It moves beyond averages to give us that critical detail needed for evidence-based decisions and public health.

Speaker 2: It really does and, and, you know, raises a fascinating question, too. Just how flexible is this methodology? Could we apply it to map other health indicators or even development indicators? Think about things where understanding age differences or these fine scale geographic patterns is really key. The potential applications seem quite broad.

Speaker 1: A really important thought to end on. The potential to apply this kind of detailed mapping much more widely. To read the full preprint article we've been discussing please do follow the link provided in the description.