Gates Foundation GOALKEEPERS

2026 GOALKEEPERS REPORT

make this MATTER

AI, EQUITY, AND THE CHOICE WE CAN'T DELAY

Goalkeepers

GOALKEEPERS IS DEDICATED TO ACCELERATING PROGRESS TOWARD THE SUSTAINABLE DEVELOPMENT GOALS.

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INTRODUCTION

AI could be a great equalizer—or widen the gap. This is not a long-range prediction. It's a present-tense choice.

BY BILL GATES
CHAIR, GATES FOUNDATION

Earlier this year, I met Gaudence Ngendahayo, a community health worker in Mwulire, Rwanda.

For families in her community, she's often the first person they turn to when someone gets sick. They trust her to answer questions with real consequences: Can this fever be treated at home? Is my child in danger? Do they need care beyond what she can provide?

Going from home to home, Gaudence often has to answer those questions without immediate access to the tests, doctors, and medicines that might be available in a well-equipped clinic.

She is very good at what she does, and her work saves lives. But her job could be easier. She could have better information when she has to make a tough call—and the tools to help her care for even more people.

I was in Rwanda to learn from health workers like Gaudence and understand what would make the biggest difference in their work. Listening to her, I kept thinking about how artificial intelligence (AI), if developed and used well, could fundamentally transform how health workers make decisions and deliver care.

The phone in a health worker's hand could help her recognize a dangerous pattern, know when to refer a patient, and anticipate which medicines her patients will need before they run out. It could connect what she sees on an individual level with the total knowledge of the wider health system. And it could help her bring better care to more people, even in places that are hard to reach.

Healthcare is only one example of how AI ***could*** improve lives. I believe AI could also have a massive positive influence on the education and economic opportunities available to people all over the world, regardless of whether they live in a wealthy district or low-income community.

My whole life, I've been focused on how innovation can expand opportunity.

I remember the start of the personal computing revolution: a time when technology became more powerful and affordable, opening up new ways to improve lives around the world.

I've lived through waves of change that felt, in the moment, like the most significant thing happening on earth.

Nothing has felt like this.

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AI is different: a technology moving faster, reaching more people than anything before it. Because of that, no one knows exactly what the future will look like even five or ten years from now, including me.

Some people have never been more worried. Others have never been so excited. I understand where both are coming from.

I've written separately about the risks that AI poses—to jobs, to security, and to our institutions. Those risks are real and deserve serious attention.

Here, I want to focus on something that often gets lost: the possibility that AI, if shaped well, could expand who has access to solutions, opportunities, and knowledge that has too often been out of reach.

AI could be a great equalizer—or widen the gap. This is not a long-range prediction. It's a present-tense choice. Here's what's at stake.

AI is different: a technology moving faster, reaching more people, than anything before it.

Where the inequities persist

EXPLORE THE DATA

We’ve made extraordinary progress. But on current trends, the gaps between rich and poor don’t close—they persist for decades.

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WE'VE MADE PROGRESS. BUT IF CURRENT TRENDS PERSIST, SO DOES INEQUALITY.

The last 25 years have shown what is possible when innovation is deliberately put to work for the people who need it most. Since the start of the 21st century, child deaths have been cut in half. Extreme poverty has declined. Deaths from HIV, tuberculosis, and malaria have fallen significantly

These gains did not happen by accident. They happened because the world invested in innovators, frontline heroes, and tools that save lives—and made sure they reached the people who needed them.

But that progress is fragile. In some places, it has already slowed, made worse by devastating cuts to funding for global health in recent years. Even still, by 2045, the world should be, on average, better educated, healthier, and less poor than it is today.

But averages hide the full story.

New data from the Institute for Health Metrics and Evaluation at the University of Washington shows health and opportunity gaps between the richest and poorest people **will stay stubbornly wide unless something changes dramatically.**

For example, in 2045, a young adult in sub-Saharan Africa is projected to still have three fewer years of schooling than their peers in high-income countries. That's big progress from where things stood 25 years ago—but it's still a gap that shouldn't exist.

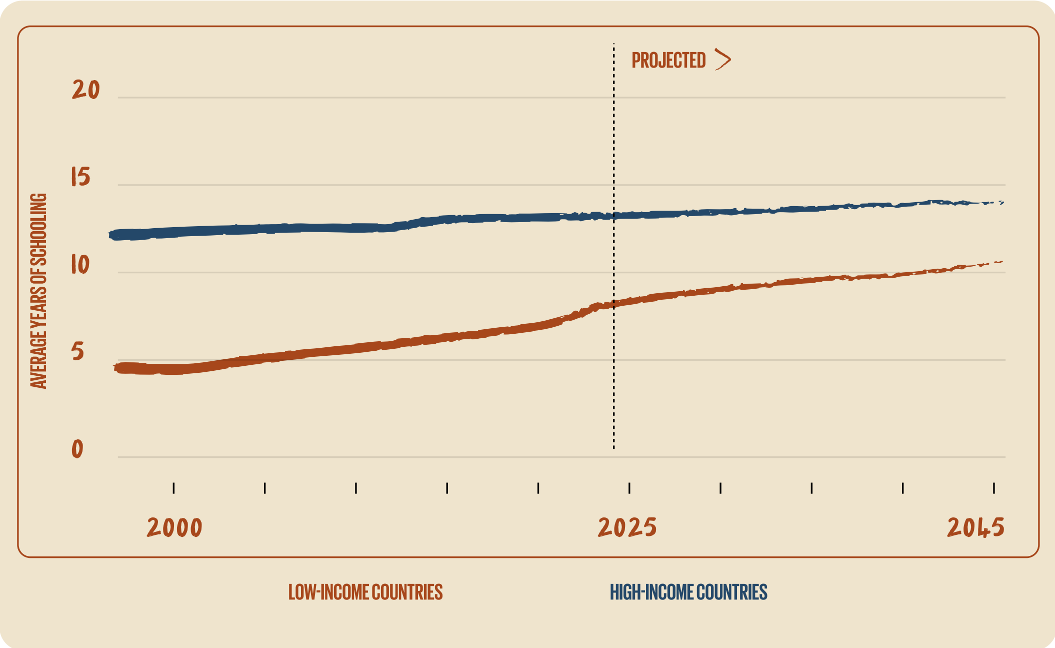
Nearly 900 million people will still be living in extreme poverty—low-income countries will have 330 times more people living in extreme poverty than high-income countries.

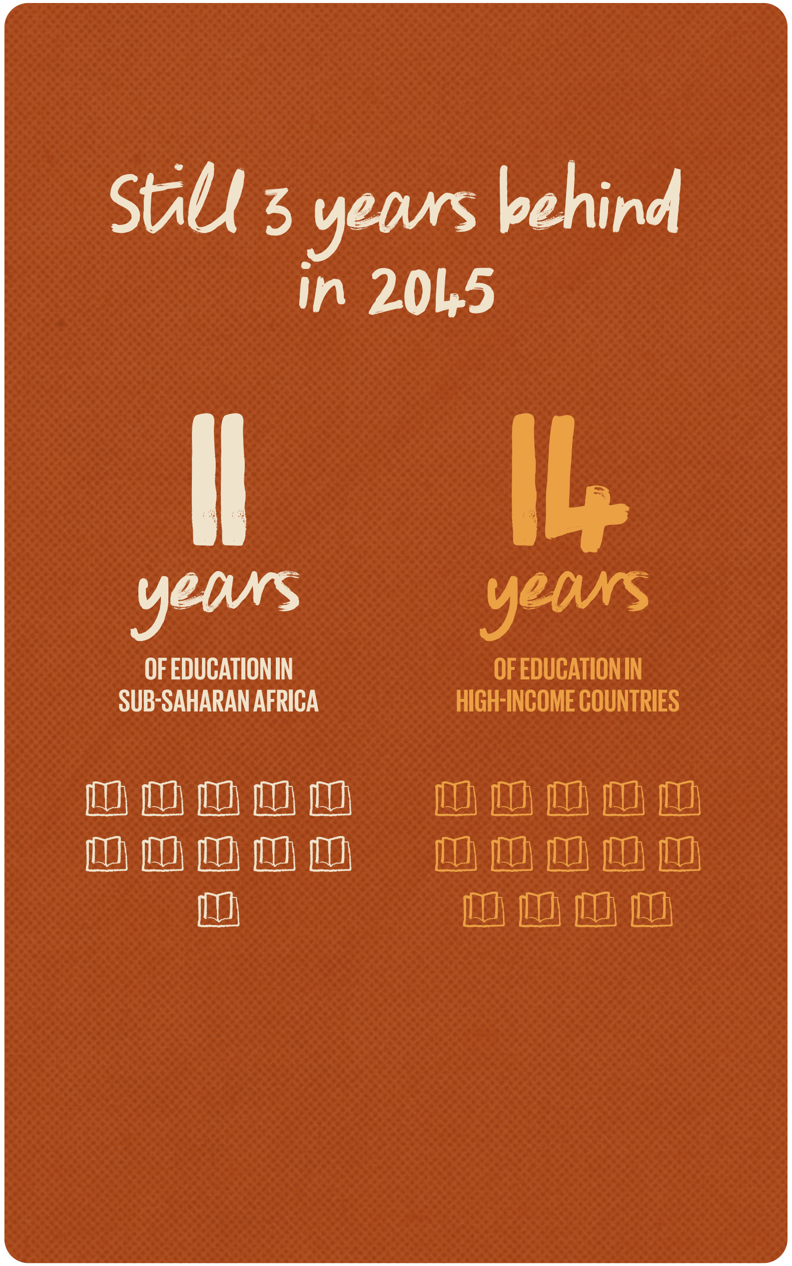
And more than 3 million children will still die each year from diseases we already know how to prevent today.

THE SCHOOLING GAP WON'T CLOSE ITSELF

Years of Schooling

HIGH-INCOME VS. LOW-INCOME COUNTRIES, 2000–2045

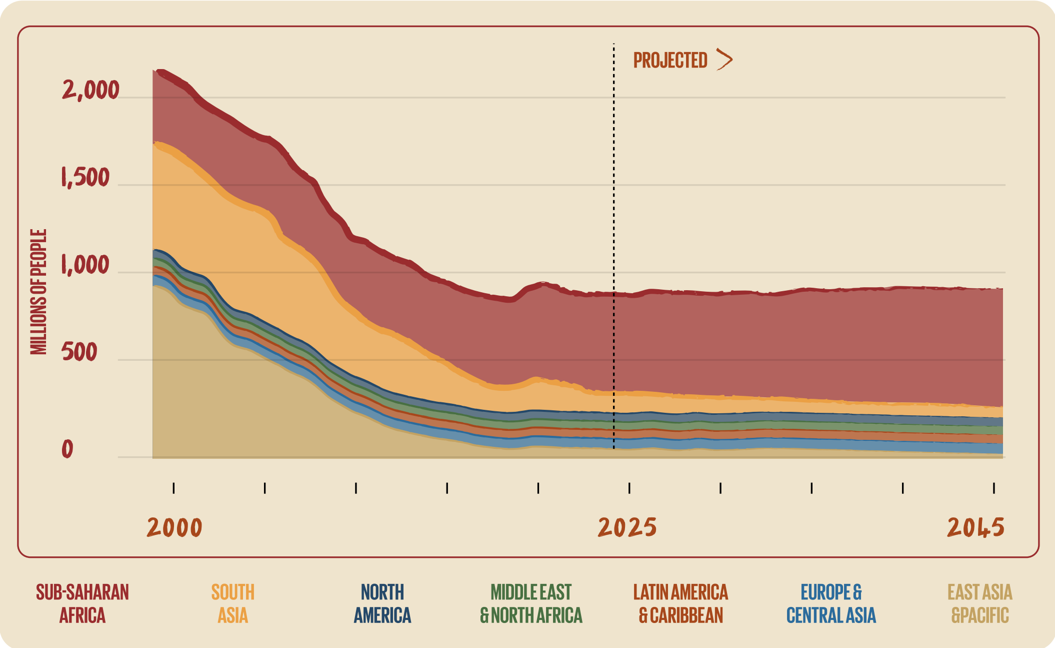


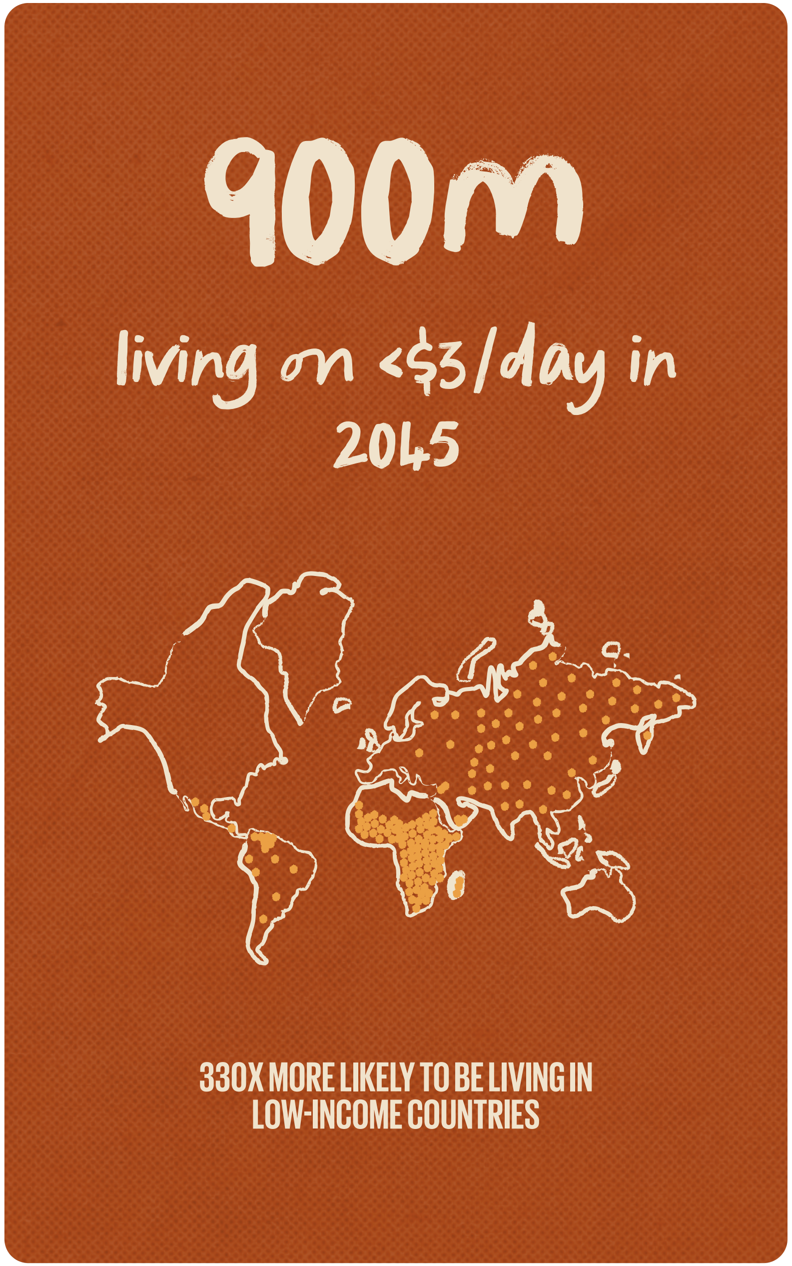


POVERTY IS SHIFTING, NOT SHRINKING

People living in extreme poverty by region

2000–2045 (MILLIONS)

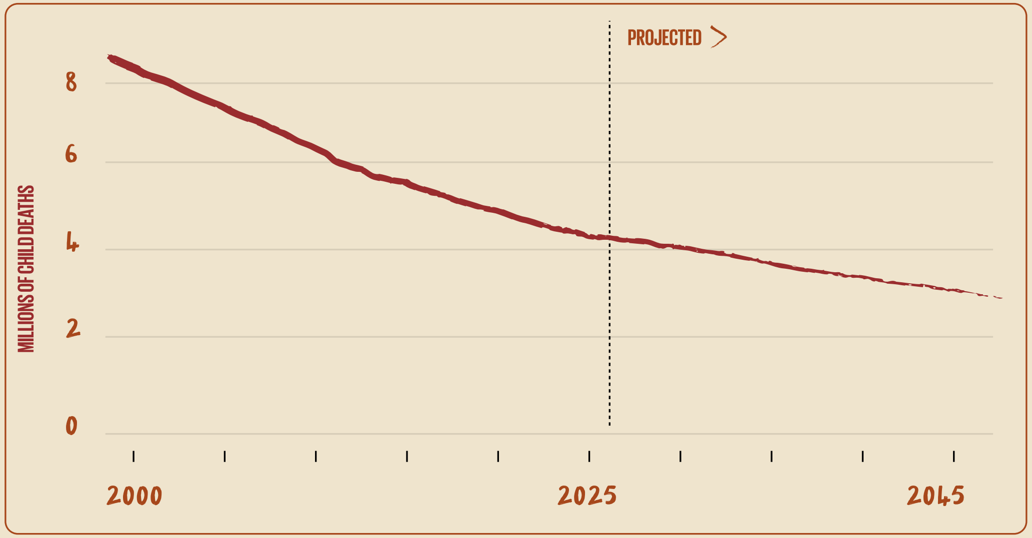




CHILDREN ARE STILL DYING FROM PREVENTABLE CAUSES

Under-5 child deaths

2000–2045 (MILLIONS)



GLOBAL

3 million

children < age of 5

WILL STILL DIE EACH YEAR FROM DISEASES WE ALREADY KNOW HOW TO PREVENT.

Behind each of these data points is a make-or-break moment for a family: a diagnosis made or missed, a harvest saved or lost, a child who learns to read or doesn't. AI is arriving at a moment when conflict is growing, diseases are surging, and resources are constrained.

This is why I care about AI. Not because it can write a beautiful line of code or plan your vacation for you, but because it can help a student get unstuck before they fall behind. It can help a farmer save their crop before it fails. And it can help parents get answers about their child's lingering fever—before it becomes a life-threatening emergency.

Of course, healthcare workers, farmers, and teachers should continue to bring their unique judgment, creativity, and care to their work. But designed well, AI can give them more support, helping knowledge travel farther, faster.

> Health and opportunity gaps between the richest and poorest people will stay stubbornly wide unless something changes dramatically.

LEFT TO THE MARKET, AI WILL BE DESIGNED BY AND FOR THE RICHEST PEOPLE IN THE WORLD

I believe that the decisions made in the next 12 to 18 months—about how AI is built, funded, and deployed—will determine whether this technology primarily benefits the people who already have the most or reaches those who have the least.

We can harness AI for good. But it won't happen by accident. After all, the market is an extraordinary engine of innovation, but a terrible guarantor of equal opportunity.

The Gates Foundation was created in part to address a basic market failure: the people with the greatest needs often have the least power to shape where innovation and investment go. For decades, that has meant lifesaving vaccines, medicines, and other tools reaching the world's poorest communities years later than they reach wealthier ones—if they reach them at all. Much of our work has been about closing that gap.

AI presents the same challenge, only at much greater speed. Left to the market alone, the most capable tools will be built first for the people and institutions most able to pay for them—not necessarily for those who could benefit most.

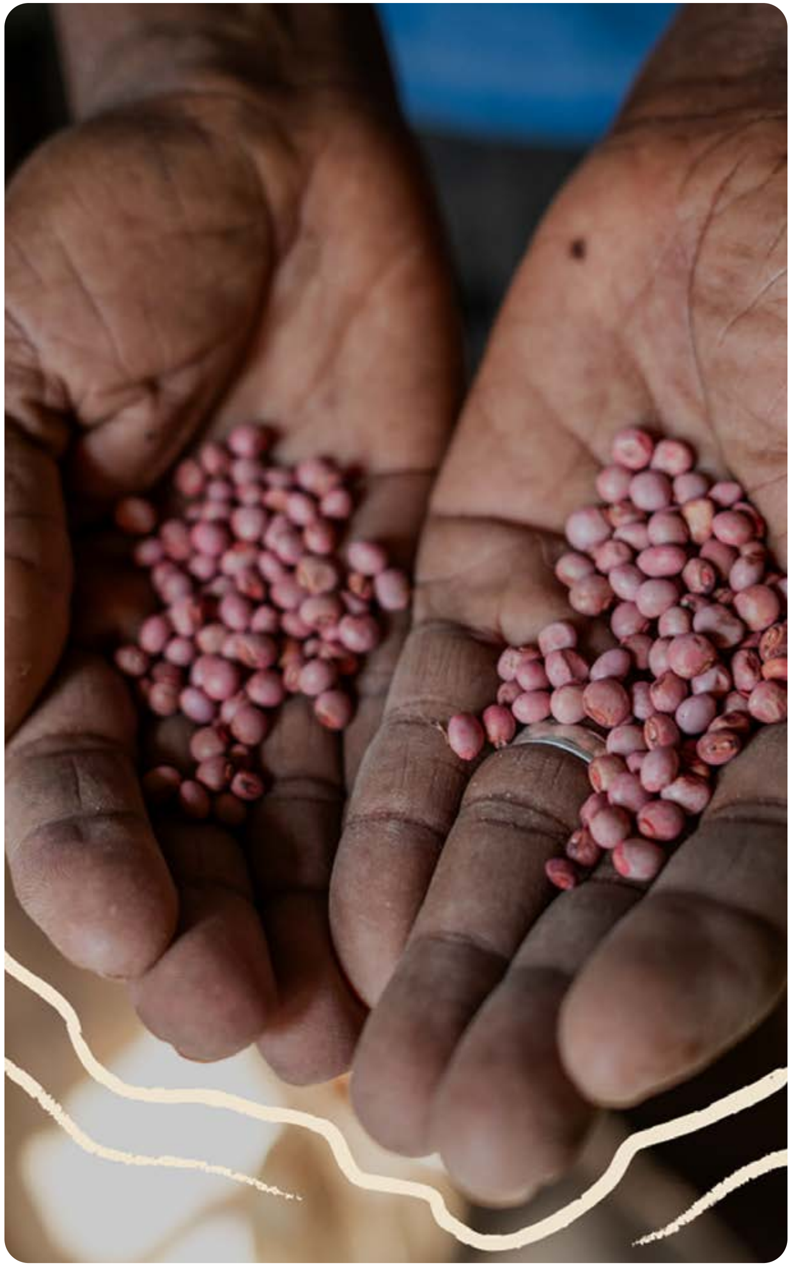
That is how inequity compounds: the technology that makes life easier, increases productivity, and sometimes even saves lives arrives first for people who already have the most.

With AI, the gap could grow even faster. AI is spreading more quickly than earlier waves of computing. With every month that passes, the distance grows. AI models get sharper and more capable for the people already using them, while standing still for everyone else.

That is what makes this moment so urgent. Things are changing rapidly, and the window to shape who benefits from AI, and how soon, is short.

The good news? Making AI useful for the people and places where it could make the biggest difference is not an evolutionary leap. It's within reach.

But it requires a deliberate, specific commitment from government leaders and the companies developing the technology: to measure success not only by what AI can do for the most profitable users but by what it can do for the people who stand the most to gain.



Where the difference gets made

IMPACT

There are only so many doctors, teachers, and farmers' advisors in the world. AI could give each of them the support to do more.

WE NEED TO REACH THE PEOPLE WHO HAVE THE MOST TO GAIN FROM AI.

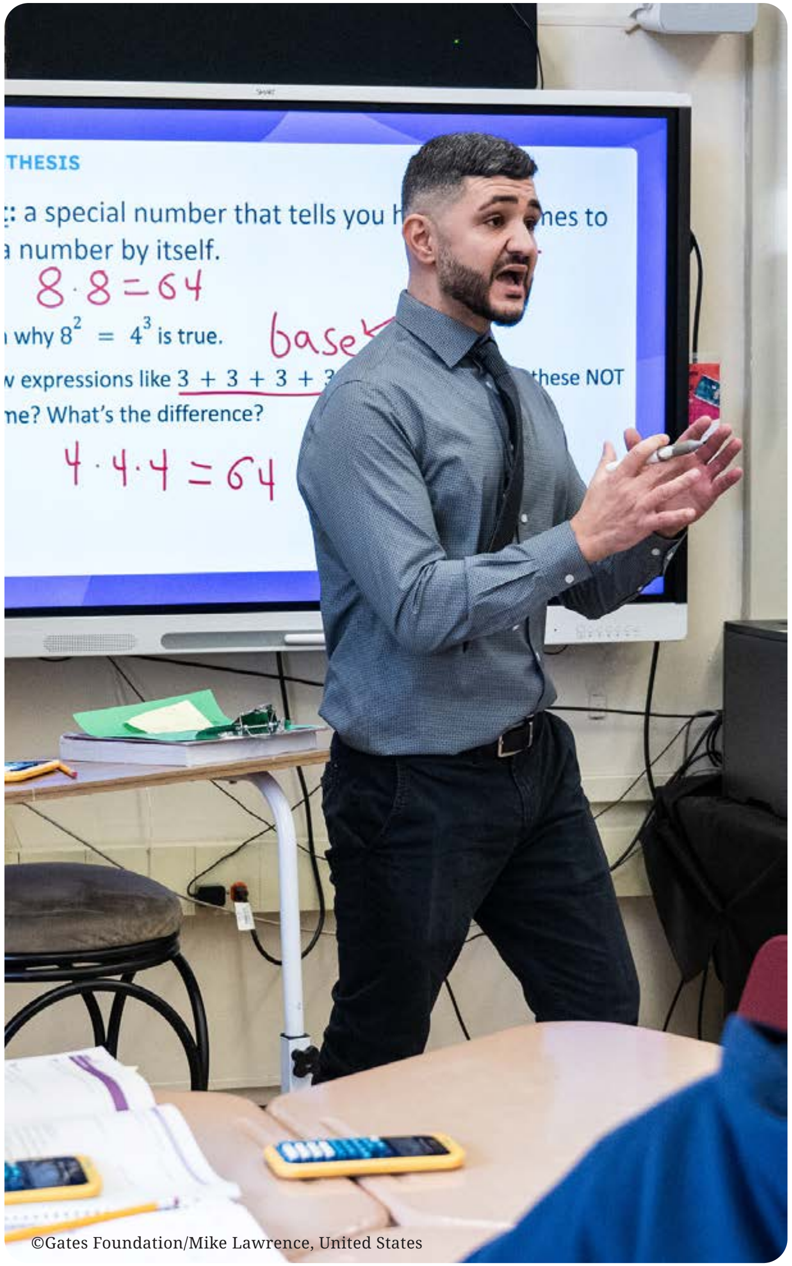
Today, many of the most promising AI tools are still in pilot mode. They need to work in all languages, on ordinary phones, and in the places where people make real-life decisions before they can be trusted to take to scale But the distance between pilot mode and scale could be much shorter than it was for earlier technologies—because if done well, AI can reach people through natural conversation, on a device already in their pocket. That means the choices being made now—by AI labs, governments, philanthropies, and local leaders—matter enormously.

Within three years, if we make the right choices, the most promising AI tools will be broadly deployed where they can make the biggest difference on most people's lives and livelihoods in health, agriculture, and education.

Across these critical issues, people in the most remote, lowest resource settings should have access to the best possible guidance at the same time as people with the most resources. To get there, AI will need to be affordable and will have to earn people's trust by protecting their privacy and working in their specific contexts.

That will require significant commitment from AI companies, governments, philanthropists, and many others. The Gates Foundation is ready to do our part. In fact, we're already working with others to ensure the potential benefits of this technology reach everyone.

> Choices being made now—by AI labs, governments, philanthropies, and local leaders—matter enormously.



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WHERE THE DIFFERENCE GETS MADE: A NURSE, A FARMER, A TEACHER

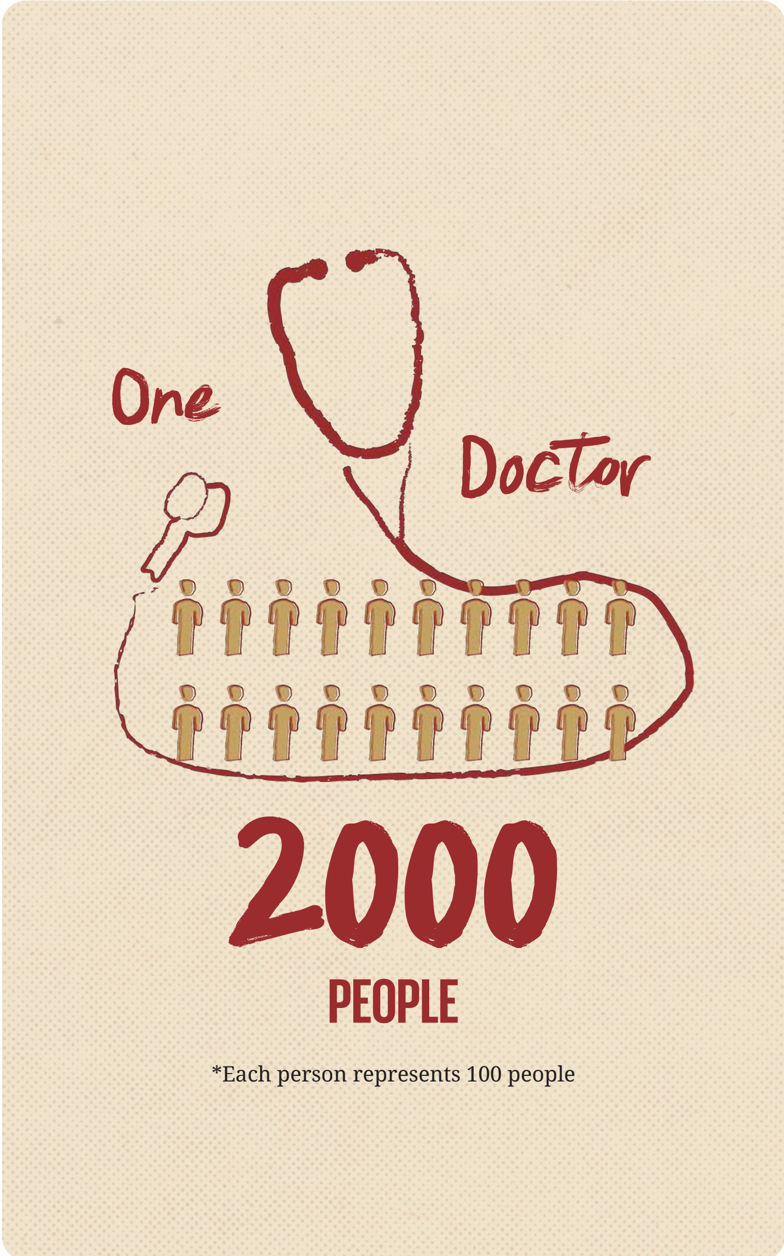
The next two decades can be a period of extraordinary progress for millions of people.

But ensuring more moms and babies survive childbirth and childhood, more families grow their incomes, and more students achieve their goals will require more than new technology. It will require getting the right knowledge to more people at the moment they need it.

I believe human ingenuity should never be replaced. But there are only so many doctors, teachers, and advisors in the world, and they simply can't reach everyone who needs support.

The shortage of doctors and trained health workers in low-income countries is dire.

In sub-Saharan Africa, one doctor cares for roughly 2,000 people. That means a single doctor is often responsible for the health of an entire town. That means many families who need urgent help have to wait, or don't get care at all. In high-income countries, each doctor cares for fewer than 200 people. To come close to that amount of access in Sub-Saharan Africa, the region would need



more than two million additional doctors. That gap will narrow over time—but far too slowly to meet the need that exists right now.

Training more doctors and health workers is essential. But patients cannot afford to wait. We need to give today's nurses, community health workers, and other frontline providers the capacity to reach more patients, and give more informed advice based on all the expertise AI can make accessible.

Gaudence Ngendahayo, the community health worker I met in Rwanda, is also a farmer. That's not unusual. In many communities, the people delivering basic health care are also earning a living, feeding their families, and taking care of everything else life demands.

Each day, farmers like her make dozens of seemingly small decisions. What to plant, when to plant it, and where? How much seed to buy? Whether to irrigate, how to respond to a pest, when to harvest, and when to take a risk and do things differently?

For many of the world's farmers, especially those with small plots of land, getting those decisions right can mean the difference between a good harvest and a lost season.

But getting them wrong does not just cost a crop. It can cost a family its income, its food supply, and its savings.

And yet, in much of the world, when a farmer is facing a failing crop, a persistent pest, or weather that is more extreme than it used to be, there's simply no one to call for advice. That's not just a problem for their family; it's a problem for everyone who relies on them for food.

Earlier this year, on a farm in Andhra Pradesh, India, I watched a farmer named Annapurna Devi take a picture of a diseased banana leaf with her phone. Using an AI tool, she received a diagnosis in her own language, along with a recommendation for how to treat the pest attack. Annapurna ordered a drone via the application to spray the recommended pesticide, which was deployed to her fields within 48 hours.

The technology was impressive. But what mattered most was much simpler: Annapurna needed to know whether she was going to lose her crop. The AI tool gave her the answer in time so she could save it.

In some parts of the world, a single teacher manages 60 or more students in each classroom, often across multiple grade levels—with almost no tools to know which children are falling behind until it's too late. AI's promise in education lies in its ability to amplify teachers' impact, helping them better understand where students are struggling, tailor support to individual needs, and spend more time on the complex, emotional work of educating the next generation. It can also serve as a tutor for every child, extending that same personalized attention beyond the classroom.

Today, a teacher might have their students fill out a worksheet or problem set, collect them at the end of class, go home, grade them, and then use the results to inform the next day's lesson plan. It's a lot of tedious work, but it's necessary if they want to tailor their next lesson to the needs of every individual student.

©Gates Archive/Ryan Lobo, India

AI tools are making that easier. Instead of collecting worksheets at the end of class, a teacher can collect them mid-lesson and, with the help of AI, get real-time guidance on who's struggling with which concepts, and how to help.

> I believe human ingenuity should never be replaced.

Make AI Matter for Everyone

CALL TO ACTION

We still have a choice. We can let AI follow the old pattern, where the people with the most resources benefit first and most. Or we can make a different choice: build it for people everywhere.

01
WORK IN EVERY LANGUAGE

02
GROUNDED IN LOCAL DATA, BUILT FOR LOCAL REALITIES

03
INVEST IN PEOPLE AND ACCESS

THREE THINGS WE NEED TO GET RIGHT.

If AI is going to help improve the lives and livelihoods of the world's poorest people, a few things need to happen in the next 12 to 18 months—and there are steps AI companies, governments, philanthropists, and many others can take right now.

I'm not suggesting there's a magic three-step solution that will make AI accessible and beneficial for everyone. But these are three fundamental building blocks we can prioritize now to make a big difference.

FIRST, AI TOOLS HAVE TO WORK IN EVERY LANGUAGE PEOPLE SPEAK.

Most of the world is invisible to today's AI models. These AI systems were trained primarily on what exists on the internet—and the internet reflects a deeply unequal world. More than 90 percent of the data used to train early, large language models came from English-language sources. The communities that stand the most to gain from AI are largely absent from the knowledge base these tools are built on. They are not just underserved. They are not in the picture at all.

Every month, AI gets sharper and more capable for the one billion (mostly English-speaking) people who already have access and stays the same for the other seven billion people on earth.

In English, leading AI speech recognition systems make errors less than 6 percent of the time. In Yoruba, that same system fails more than 60 percent of the time.

It is not just everyday vocabulary that matters. A striking example comes from Malawi, where a woman in labor might say her "water has broken" in Chichewa. Translated directly to English, it would sound like she has simply "thrown away water." That mistranslation could be the difference between timely, urgent medical advice and tragedy.

If AI is going to improve health on a continent with more than 2,000 languages, it has to understand what and how people actually speak—their dialects, accents, and slang, too.

This requires investment in local language datasets and evaluations tailored to how people use language in the places these tools are meant to serve.

WORK IN EVERY LANGUAGE

SECOND, THESE TOOLS HAVE TO BE GROUNDED IN LOCAL DATA AND BUILT FOR LOCAL REALITIES.

Language is only the beginning. An AI tool built for a commercial farmer in Iowa is not necessarily ready for a smallholder farmer in Ethiopia. Smallholder farmers often grow several crops on a small plot, rely on family labor, have limited access to credit and insurance, and make decisions in conditions where a failed harvest can threaten both their income and their family's food supply. An effective tool must understand that reality—as well as the crops they grow, the pests they face, the cost and availability of inputs in local markets, and what the weather is likely to do in their specific region.

The same is true in health. Global health guidelines already exist. The work now is making those guidelines locally relevant: incorporating the right epidemiology for a specific country, the treatment options actually available in that health system, the operating conditions of the clinics where health workers are making decisions. A community health worker in Rwanda examining a baby with a fever faces different questions than a clinician in a well-resourced hospital—and the AI supporting her needs to reflect that.

This is a data problem as much as a design problem. Building AI that works in every setting requires collecting the right local data—health records, farming outcomes, weather trends, student learning patterns—from the places and populations the tools are meant to serve. Countries should be able to decide on the best way to manage and protect that data, including how it is stored and on what terms it is shared, and with whom.

Both closed and open AI systems have a role to play—what matters is not which model a country uses but whether it works for their specific needs, at a cost and on terms they can sustain.

The good news is that this investment compounds over time. AI systems that start with good local data and are tested against real-life decisions—not just impressive demonstrations—get better the more they are used. People trust tools they've personally tried. The real test isn't whether it sounds impressive, but whether it actually works.

02

GROUNDED IN LOCAL DATA, BUILT FOR LOCAL REALITIES

THIRD, INVEST IN THE PEOPLE AND ACCESS TO MAKE AI WORK.

Whether a promising AI pilot actually helps millions of people depends on two things the world isn't investing in enough: people and access.

On people: the communities with the most to gain need local AI leaders at every level—policymakers and technologists who shape how AI enters their countries, and doctors, agronomists, teachers, and data scientists who understand these tools deeply enough to evaluate them, adapt them, and hold them accountable. That means creating real pathways to technical AI expertise in these countries: college programs, master's degrees, and hands-on training that give the next generation the knowledge to lead this work themselves, not just use the tools someone else built.

On access: none of this is possible without meaningful access to AI models and the ability to run them where they're needed. Right now, that access is highly concentrated in wealthy countries—and the barriers go beyond price alone. Changing that will require a mix of approaches: price reductions, commitments from AI companies to make their models and computing resources available, and government and philanthropic funding, among others.

The goal is not for AI to be designed somewhere far away and handed to communities to figure out. It is for the communities with the most to gain to develop the knowledge and the agency to shape how it works for them.

INVEST IN PEOPLE AND ACCESS

MAKING THIS MATTER FOR EVERYONE

A world of greater productivity should make people’s lives better. But history has shown us that greater productivity and more resources do not automatically produce better life outcomes—more purpose, ease, or peace. The choices being made now about AI are choices about what kind of world we want to leave the next generation.

Imagine what that could look like.

A pregnant woman could ask a question in her own language at home, late at night, without traveling miles to a clinic. A farmer could catch one sick plant before it becomes a lost harvest—and another season of hunger. A student who gets stuck on a lesson could get help getting unstuck, while her teacher gets a clearer picture of where she needs support.

These are not small things. They’re the moments that decide whether progress reaches a family when it matters, or not at all.

AI is moving fast. The market will not wait. The systems being built now will shape who benefits for years to come.

We still have a choice—AI companies, governments, and philanthropies. We can let AI follow the old pattern, where the people with the most resources benefit first and most. Or we can make a different choice: build it for people everywhere.

Let’s make this matter.

GUEST ESSAYS

Four AI tools. Four frontline workers. Already making a difference.

Real Work. Real Impact.

©Gates Archive/Mansi Midha, India

EARLY EVIDENCE SHOWS WHAT'S POSSIBLE.

The people making critical decisions every day—on farms and in hospitals, classrooms, and communities—see the challenges and opportunities of AI even more clearly than I can. They know what it means when a mother has no expert clinician nearby, when a farmer has no one to call, or when a teacher is trying to help 30 students who are all struggling in different places.

Early evidence suggests that tools built for frontline workers are already making a big difference. Here are four tools I'm excited about—ones that show what becomes possible when frontline workers have the support they need.

In the essays that follow, you'll hear from four people using these tools in health, agriculture, and education. They understand not only what AI can do but what it will take to make it useful in the real world.

PENDA HEALTH

+16

percentage points

IN DIAGNOSTIC ACCURACY

In Nairobi, Kenya, a network of affordable primary care clinics called Penda Health has embedded AI directly into clinical visits—giving clinicians real-time guidance on diagnosis, drug dosing, and when to escalate as they see patients. The clinician sees the suggestion and decides when and how to act. Diagnostic accuracy has improved by 16 percentage points.

KIDDOM ATLAS

+6

months

OF ADDITIONAL LEARNING IN A SINGLE SCHOOL YEAR

In the United States, the AI tool Kiddom Atlas helps teachers determine how to best support each student to unlock math skills and move forward. Students complete a short diagnostic test at the end of each lesson; Atlas gauges each student's level of understanding and delivers a ready-made plan for the next lesson to the teacher. In early pilots across 21 middle schools, grade 7 students gained the equivalent of six additional months of learning in a single school year.

GEMINI GUIDED LEARNING

+1.7

years

OF LEARNING

In Sierra Leone, teachers using an AI tool called Gemini Guided Learning are getting a new kind of support in the classroom. While teachers lead the lesson, students can turn to Gemini for help with math. When students ask for an answer, the tool responds with a question to help them work through and understand the concepts. In an eight-week trial across 12 schools, students made the equivalent of up to 1.7 years of typical learning progress.

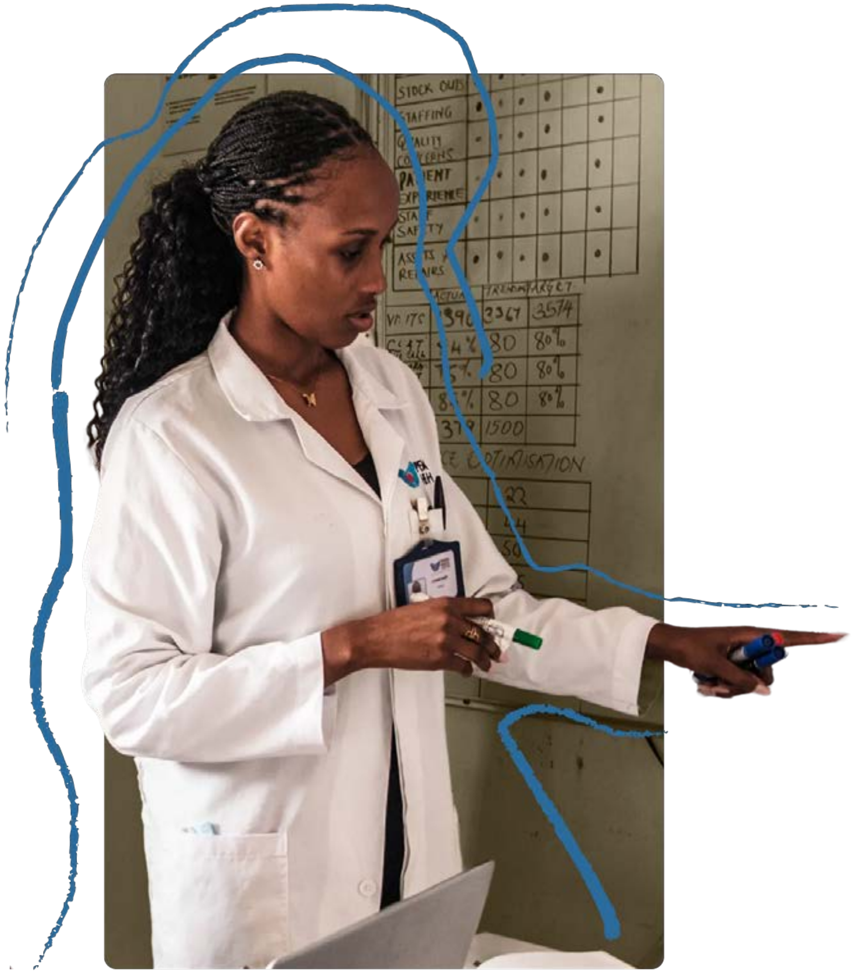
MAHAVISTAAR

<0.18

cents

PER FARMER

And in India, the state of Maharashtra has bult a free AI advisory service for farmers—called MahaVISTAAR—directly into government infrastructure. Through an app, voice calls, and chat, farmers can ask questions about their crops, the weather, and pest management in their own language and get verified, localized answers. More than 740,000 farmers have already joined, with 70,000 new users signing up every month. This service costs the government less than 18 cents per farmer.



I'M STILL THE PROVIDER. AI HAS MY BACK.

By Vyonne Njeri

CLINICAL OFFICER AT PENDA HEALTH, NAIROBI, KENYA

The place that inspired me to study medicine wasn't a hospital—it was a church.

It was during a visit to see my uncle, a priest in a small, East Kenyan town called Modogashe. One day, I went to the parish to bring him his lunch and saw a nurse performing a suture on an elderly woman's leg. I looked outside and saw a long line of patients, all waiting for their turn. His parish housed a small local clinic, staffed by a single nurse—the only medical practitioner in the area.

I turned to my uncle right then and told him I wanted to study medicine.

In rural communities like Modogashe—or Laikipia County, where I grew up—many patients don't live anywhere near a clinic. Those who do often can't afford regular visits, so they develop chronic, preventable diseases that cost even more to treat in the long term.

Clinicians, meanwhile, face overwhelming patient loads, compounding the stress of a job where a single mistake could cost someone their life. That's why the clinic I'm at now, Penda Health, built a safety net.

It's called AI Consult: a copilot embedded directly into the same digital records system we use for every appointment. As we enter information on the patient's medical history, symptoms, test results, and our recommended treatments, the tool double checks our work. Most of the time, it shows a green check mark. But if we overlook a certain symptom or prescribe an inappropriate medication, it might return a yellow or red flag, prompting us to take another look.

I once had a mother bring in her four-month-old with a fever and runny nose. It looked like a simple cold or allergies, so I prescribed acetaminophen. But when I typed that in, a yellow flag from AI Consult popped up: the child's respiratory and heart rates were elevated. That could just be the fever, but it could also be something else. So I listened to the child's chest again—and this time, I heard something concerning.

I told the mother she should have her child screened for congenital heart disease. When I followed up a week later, she said their pediatrician had indeed found a congenital defect—a hole in the heart. If this hadn't been caught, it could have been deadly. But with the right treatment, most children with these kinds of heart defects live healthy, normal lives.

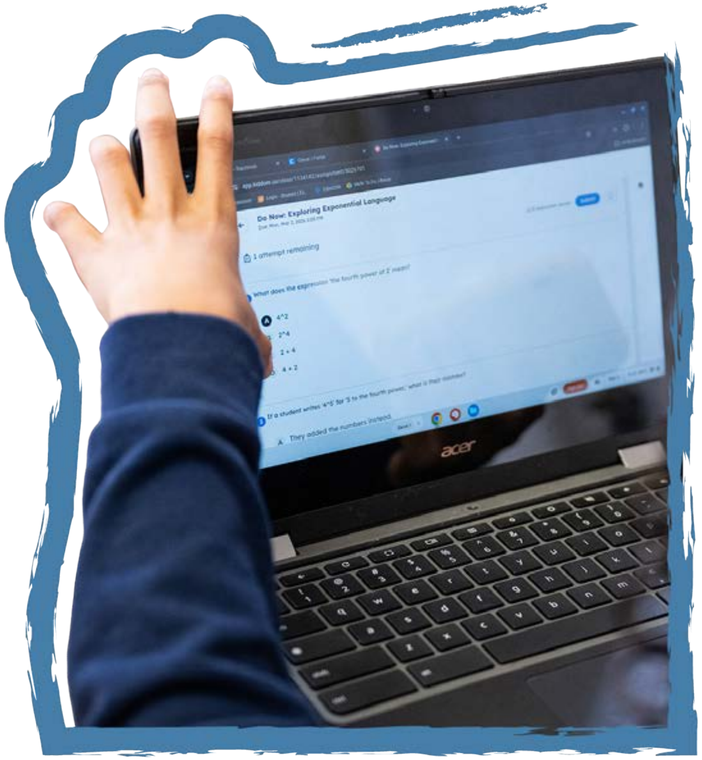
Across all our clinics, we've seen a 16 percent drop in diagnostic errors and a 13 percent reduction in treatment errors since we started using AI Consult.

It's still far from perfect. I have some concerns about newer clinicians over-relying on AI instead of developing their own clinical judgment. And I've occasionally noticed that certain information—like local drug formularies or protocols for pediatric care—is missing from the tool.

AI can't replace health workers. I was the one who examined that baby. I was the one holding the stethoscope and talking to the mother. But when you're the sole person responsible for someone's health, a second opinion can save someone's life.


©Gates Archive/Brian Otieno, Kenya

"AI can't replace health workers... But when you're the sole person responsible for someone's health, a second opinion can save someone's life."



Arnelle Banks was not available for photography or filming.
Her essay appears in her own words.

MEETING EVERY STUDENT'S NEEDS

By Arnelle Banks

TEACHER, NEW YORK CITY, UNITED STATES

No middle schooler wants to feel like they're different from all the other kids. But I was. I was born and raised in Jamaica and moved to New York in seventh grade. Thankfully, I had a math teacher, Ms. Nolan, who never made me feel like an outsider. She even talked to the other kids to make sure I never sat by myself at lunch.

Today, I teach seventh grade math too. Many of my students are like me: immigrants from another country who might be enrolling in a U.S. school or learning English for the first time. But my classes are structured like any other.

When students walk in, there's a warm-up problem on the board. Then we move on to a lesson, followed by independent or group practice. And we close with an "exit ticket": one last question to see if they understood the lesson, which they hand to me on their way out. After class, I go through their exit tickets by hand to see who understood the concepts, and who's struggling.

Like many teachers, my greatest challenge is differentiation. Because my classes are fairly large, I tend to adapt lessons for the students who are struggling, so I can make sure they catch up before we introduce a new concept. But that sometimes means I'm not doing enough to challenge the students who are already at or above grade level.

That's where an AI tool, Kiddom Atlas, made a huge difference. Now, instead of giving everyone the same warm-ups and exit tickets, Kiddom tailors those problems to meet students where they are. If they're struggling with a concept, it gives them more practice on it. If they've got it, it challenges them with something harder.

At the end of each day, it gives me summaries of each student's progress, and can even show me precisely where there are gaps in their understanding. For instance, it showed me that one of my seventh graders was actually struggling because of a concept they misunderstood from the fourth grade. I don't think I would have realized that by myself.

Before Kiddom, I was always skeptical about doing math on a computer. As teachers, we know that when students write things down by hand, they're more likely to internalize the lessons and procedures. Even now, kids still spend most of my period with pencil and paper. But just using Kiddom for warm-ups and exit tickets—about 5 minutes of class time each—has made a huge difference.

I used to be known as the "bag lady" who always went home with a pile of ungraded papers sticking out of my bag. Now, the only thing in there is my laptop.

More important, my students are excelling. Over a single year, I've seen all of them rise to or above grade level. And though they don't know it yet, by the time you read this, many of my once-struggling seventh graders will have started their eighth grade honors class.

There are still issues to work out. I wish my students could annotate questions on the computer the same way I teach them to on paper. And I sometimes catch flaws with the practice questions themselves. Kiddom has always been responsive when I raise these issues, while I can't say the same for every platform.

AI can never replace a real teacher. It can't make a classroom feel like a home, or make sure a new student doesn't sit alone at lunch. But even though no middle schooler wants to feel different from everyone else, the truth is, they are. Every student has unique needs. And Kiddom Atlas has helped me support those needs better than I ever could have alone.

©Gates Foundation/Mike Lawrence, United States

> Kiddom tailors problems to meet students where they are.

A TOOL THAT'S HELPING CHANGE THE NUMBERS

By Momodu Orgber Bah

TEACHER, LUNGI TOWN, SIERRA LEONE

When I was a student, it was rare to see a textbook.

In the 1990s, when I was in secondary school, my country was in the middle of a civil war. Resources were scarce, and my education was constantly interrupted. Every once in a while, my classmates and I would see a rich kid walking around with a textbook, and we'd try to steal a few pages out of it so we could study too.

After the war, I studied masonry. But after working a few odd jobs, a local Catholic priest—Father Dominic—took a chance on me and asked me to teach construction to ex-combatants.

As it turned out, teaching was my calling. Today, I teach mathematics at a junior secondary school that not only has a library full of textbooks but a computer lab. I couldn't be happier; my students have access to technology. So when I was invited to a workshop hosted by EducAid Africa about Gemini's Guided Learning AI tool, I was excited about what it could mean for my class.

The impact was even greater than I imagined.

In Sierra Leone, people think of mathematics as something that only geniuses study. This belief has created a real problem for the entire country. After all, mathematics is a core subject for university and a foundational skill for countless professions.

I've been teaching mathematics for 20 years now, and usually, only around 55 to 60 percent of my students pass the class.

Since we started using AI to support our instruction, that number has gone up to 100 percent.

It's not just my class. In a recent pilot program, students who used Guided Learning saw one to two years of educational progress in just eight weeks. Students—including mine—also reported enjoying math more, and I've seen them engage with the lessons more deeply.

The AI Guided Learning tool is fairly easy to use. Every day I write the topic of our lesson on the whiteboard. Students enter that topic, as well as their country and grade level, into the program, and it gives them guided practice questions. While they work on the questions, I make my rounds and check on anyone who seems to be struggling. Once they're done, we leave the computer lab, head back to the classroom, and I continue teaching as usual. So what they don't learn from Gemini, they learn from me—and vice-versa.

What really excites me are the applications beyond the classroom. If my students want to get more practice in, I tell them to borrow their parents' phones—with supervision from their parents, of course—and use Gemini like a personal tutor.

There are still challenges when it comes to AI, of course. I worry about how kids might use these technologies without supervision. And a lot of my students don't have internet access at home, so they couldn't continue studying even if they wanted to.

But then I think back on my own childhood. Not only did I not have internet access, I often didn't even have light. I remember studying outside by moonlight when I couldn't find a lantern. I'm so excited about the opportunities my students have today; opportunities I could never have imagined as a student.

©Gates Archive/Abdul Kanu, Sierra Leone

I couldn't be happier my students have access to technology. The impact was even greater than I imagined.

BETTER ADVICE, BETTER HARVESTS

By Dipali Kalbhor

SMALLHOLDER FARMER AND ENTREPRENEUR, MAHARASHTRA, INDIA

Farming is in my blood. I come from a family of farmers. I graduated university with a degree in agriculture, and my first venture after graduating, raising goats, was a success. I thought I knew everything. So I took my savings and started a poultry business. It was a disaster. I ran into one problem after another. And before I knew it, I'd lost thousands of chickens.

After that, I fell into a deep depression. It took a while to pull myself back out. But thankfully I wasn't alone. I have a great team behind me. With their support, I started a new business: beekeeping. We began with just 30 bee boxes. Today, we have more than 1,000 boxes, and a team of 12 people. We sell to local businesses and individuals and even provide pollination services to other farmers—reducing their reliance on other regions for pollination.

I've learned a lot—both in the field, and in the classroom. But one of the biggest lessons is that you can only do so much alone. If you want to really grow, you need not only a good team, but access to the right information too. That's why I was excited to learn about MahaVISTAAR during a regular training session with our local agricultural extension officer.

MahaVISTAAR isn't the first AI tool or app I ever tried, but it is the first dedicated specifically to farming. It provides advice on crop prices, changing weather patterns, and pest control. But my favorite part might be the fertilizer calculator. All I have to do is put in what I'm growing and what kind of compost I'm using, and it tells me exactly how much fertilizer to use and when. That single feature has helped me reduce fertilizer usage by around 15 percent—savings that allowed me to start another new business growing mulberries, which I sell to local silk farmers.

Since the app was developed by the government, it understands numerous local languages and dialects. I can even use it to check what government support programs I'm eligible for, compare the selling prices of different crops, look up contact information for local agricultural officials, and so on. I probably use it to help me make decisions at least two or three times a day.

I'm one of the youngest farmers in my region. You might think that would be a disadvantage, but I've learned the hard way that you can't build a business like this alone. You need a good team and the right tools. As long as you have both, there's no failure you can't overcome.

©Gates Archive/Ryan Lobo, India

One of the biggest lessons is that you can only do so much alone. If you want to really grow, you need not only a good team, but access to the right information.

A Final Thought


©Gates Archive/Alissa Everett, Kenya

AI can make the difference. A diagnosis made. A harvest saved. A Child who learns to read.

make this matter

Sustainable Development Goals

TRACK THE SUSTAINABLE DEVELOPMENT GOALS

In 2015, 193 world leaders agreed to 17 ambitious Sustainable Development Goals (SDGs) to end poverty, fight inequality, and improve health by 2030. Goalkeepers works to accelerate progress toward these goals, focusing on Goals 1 to 6.

Each year, the Goalkeepers Report tracks 18 key indicators—from poverty to education—offering the latest estimates on where innovation and investment are driving progress, and where we're falling short. These data remind us that progress is possible but not inevitable.

With just four years left, the world is off track. It's clear: urgent action is needed to meet the SDG targets and create a more equitable, safer future for all by 2030.

INTERACT WITH THE DATA

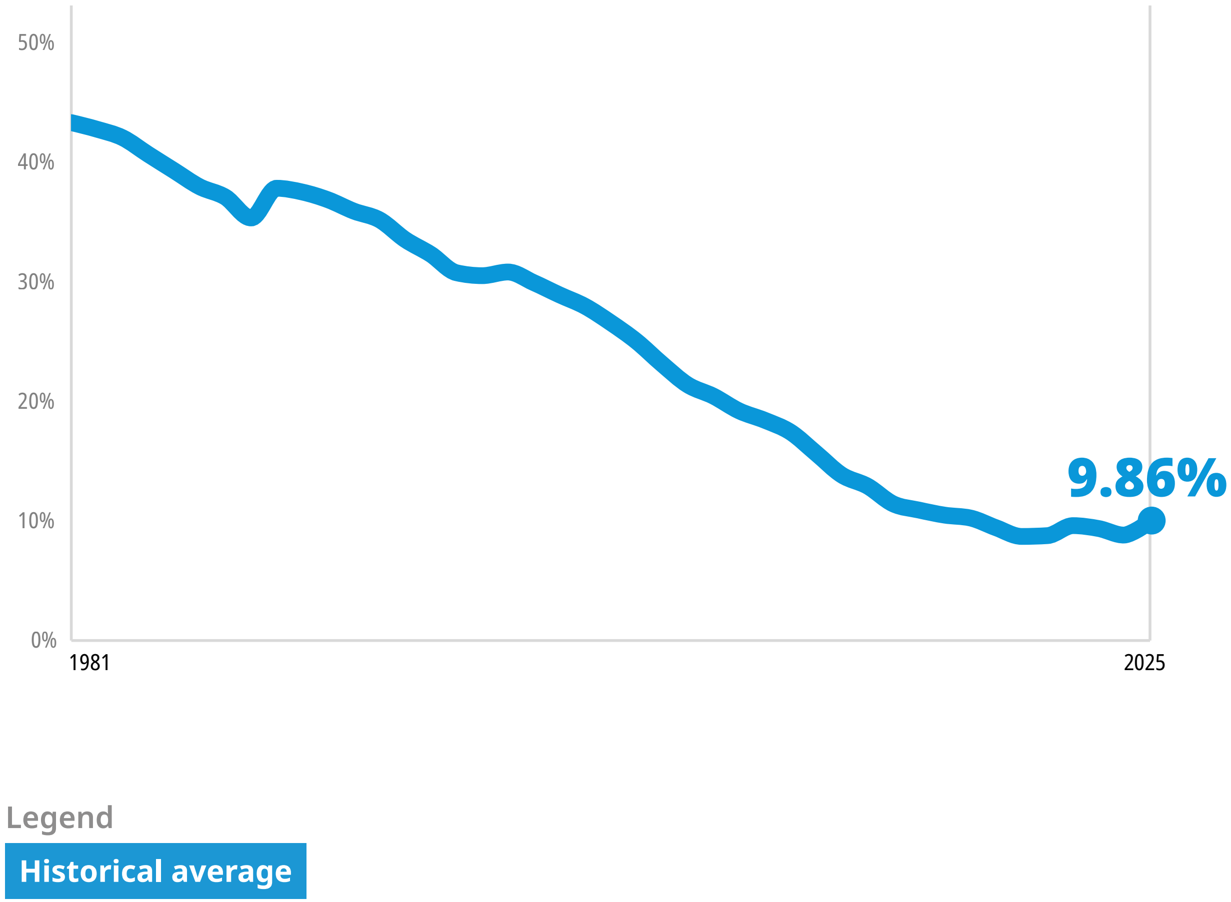
Visit our website to view an interactive version of these charts and access the raw data. gates.ly/2026GK-SDGData

POVERTY

SDG TARGET 1.1
ERADICATE EXTREME POVERTY FOR ALL PEOPLE EVERYWHERE.

Almost 10% of the global population, or 808 million people, lived on less than the US$3.00 per day poverty line in 2025. The World Bank estimates that nearly 9% of the world's population will remain in extreme poverty by 2030—that's 757 million people in extreme poverty.

Percentage of population below the international poverty line (US$3.00/day)

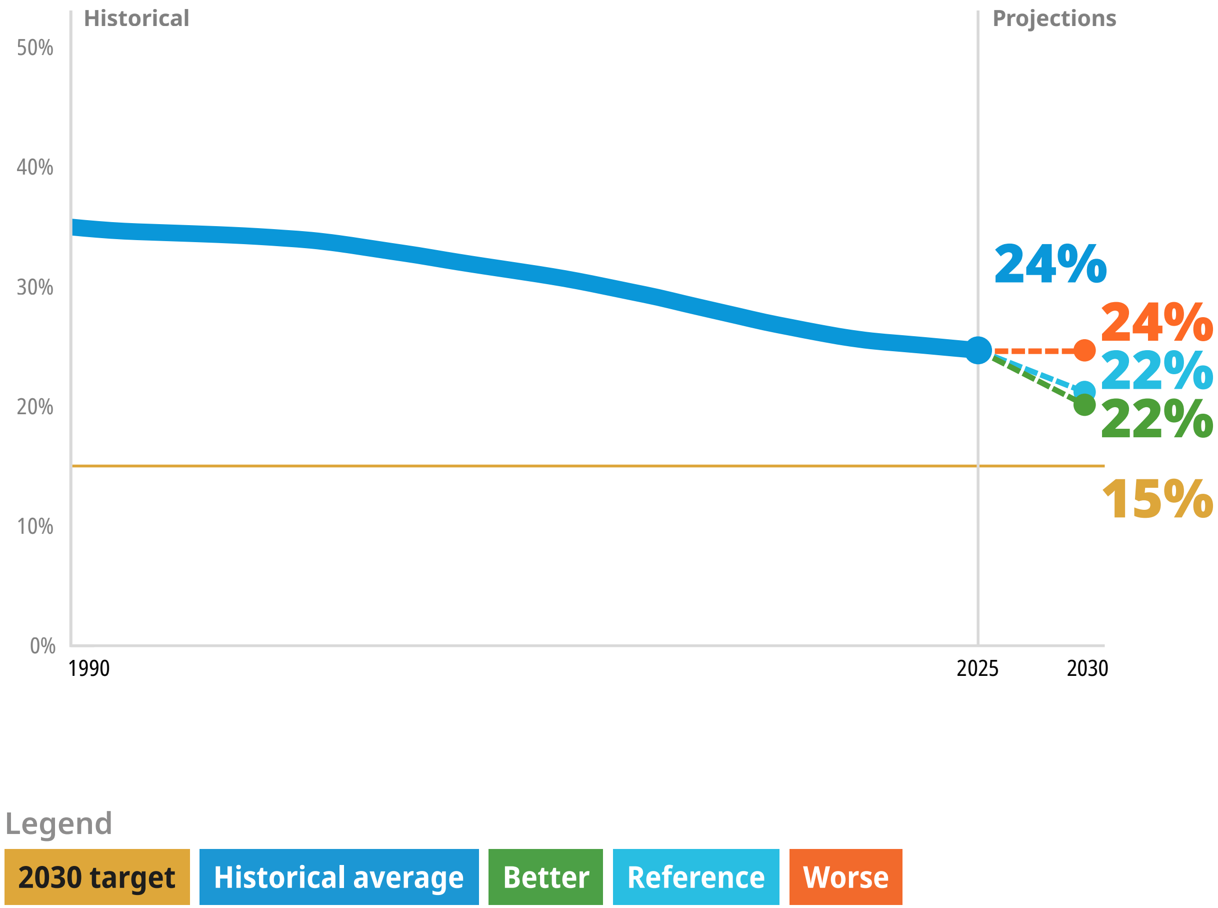


STUNTING

SDG TARGET 2.2
END ALL FORMS OF MALNUTRITION, INCLUDING ACHIEVING THE INTERNATIONALLY AGREED-UPON TARGETS ON STUNTING AND WASTING IN CHILDREN UNDER 5.

Stunting prevalence globally among children under age 5 stalled at 24% in 2025, including more than 30% prevalence in South Asia and sub-Saharan Africa, and is projected to decline only a small amount, to 22%, by 2030—missing the 2030 stunting target of 15%.

Prevalence of stunting among children under age 5



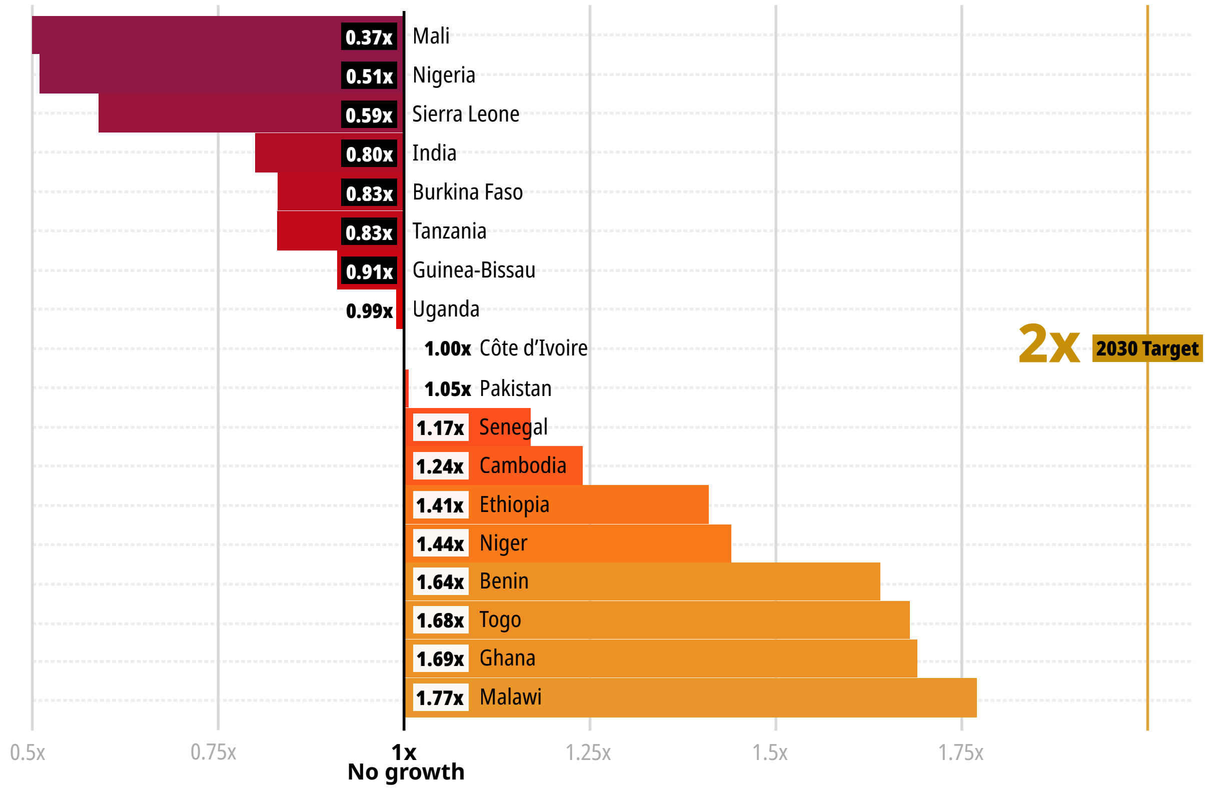
AGRICULTURE

SDG TARGET 2.3
DOUBLE THE AGRICULTURAL PRODUCTIVITY AND INCOMES OF SMALLHOLDER FOOD PRODUCERS, IN PARTICULAR WOMEN, INDIGENOUS PEOPLES, FAMILY FARMERS, PASTORALISTS, AND FISHERS.

Smallholder producers lag large-scale producers and face an income and productivity crisis. Innovations that allow small farmers to do more with their limited resources are needed in an environment where extreme weather events, conflict, and economic volatility pose serious challenges to their food security. Efforts are underway to bolster the scale-up of agricultural statistics collection to continue learning more.

Note: Country growth rates are not comparable since they are calculated over different year ranges. All date ranges can be found in data sources.

Rate of average annual income growth from agriculture for smallholder food producers



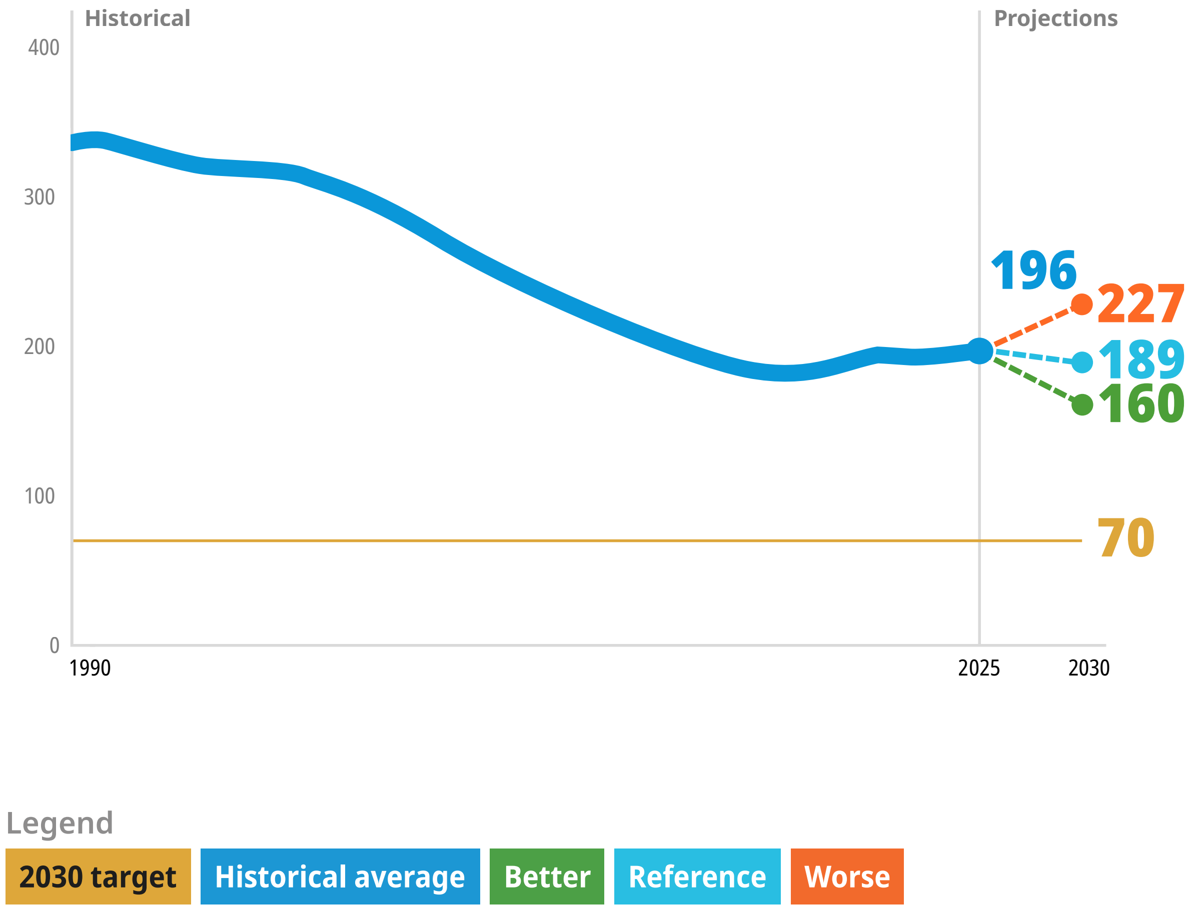
3 GOOD HEALTH AND WELL-BEING

MATERNAL MORTALITY

SDG TARGET 3.1
REDUCE THE GLOBAL MATERNAL MORTALITY RATIO TO LESS THAN 70 PER 100,000 LIVE BIRTHS.

Progress on the global maternal mortality ratio has stalled since 2016. In 2025, the maternal mortality ratio was 196 per 100,000 live births. The 2030 projection estimates 189 maternal deaths per 100,000 live births. Achieving the target by 2030 will require an annual rate of reduction of 18%, a rate much faster than historical trends.

Maternal deaths per 100,000 live births

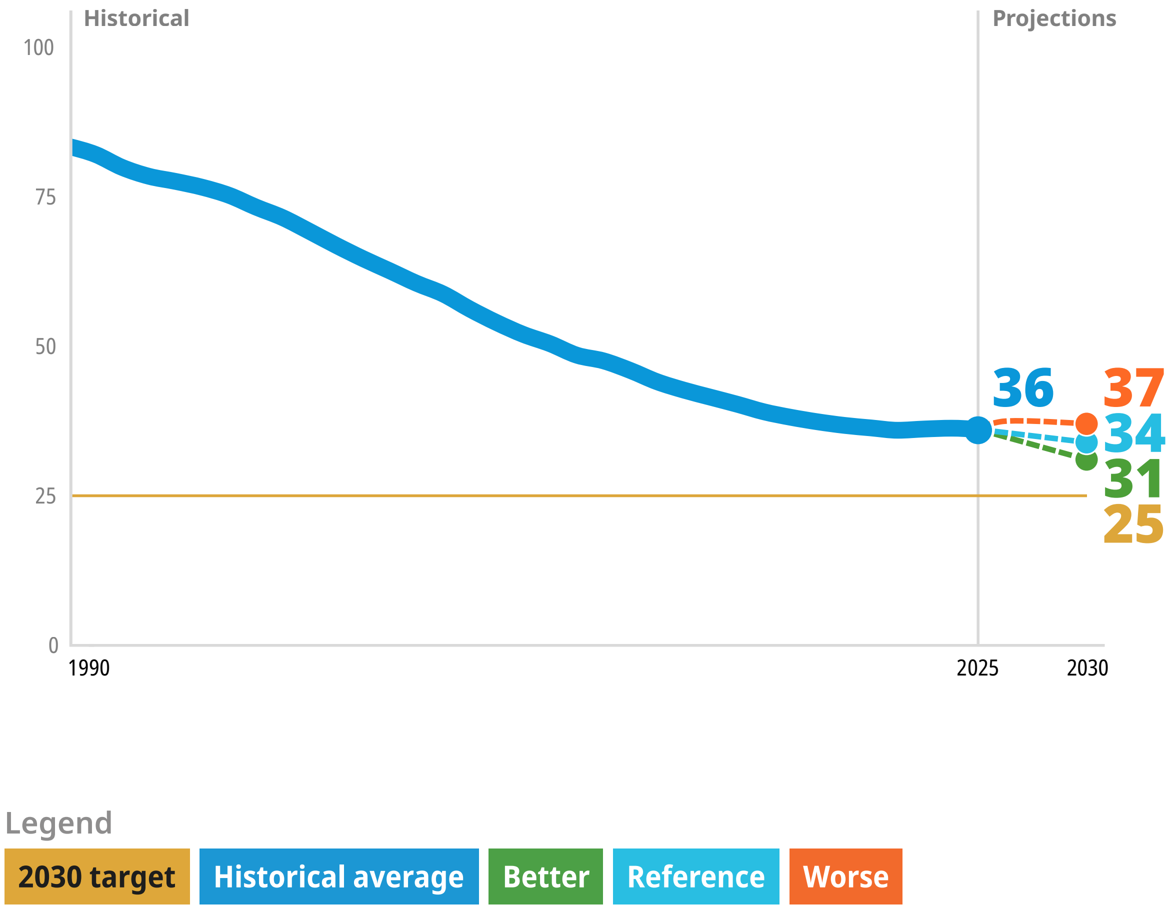


UNDER-5 MORTALITY

SDG TARGET 3.2
END PREVENTABLE DEATHS OF CHILDREN UNDER 5 YEARS OF AGE, WITH ALL COUNTRIES AIMING TO REDUCE UNDER-5 MORTALITY TO AT LEAST AS LOW AS 25 PER 1,000 LIVE BIRTHS.

Child mortality has been slowly declining, reaching 36 deaths per 1,000 live births in 2025. By 2030, the projected child mortality rate is estimated to reach 34 per 1,000 live births—still missing the target of 25 child deaths per 1,000 live births.

Under-5 deaths per 1,000 live births



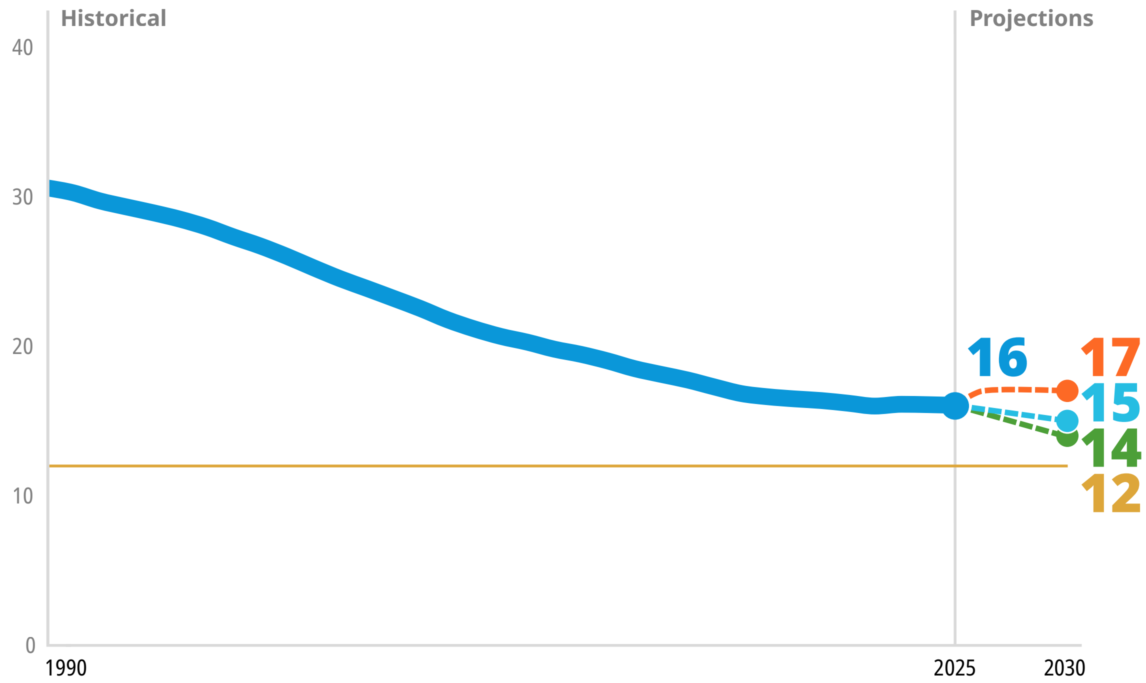
3 GOOD HEALTH AND WELL-BEING

NEONATAL MORTALITY

SDG TARGET 3.2
END PREVENTABLE DEATHS OF NEWBORNS, WITH ALL COUNTRIES AIMING TO REDUCE NEONATAL MORTALITY TO AT LEAST AS LOW AS 12 PER 1,000 LIVE BIRTHS.

Progress in reducing neonatal mortality has slowed, reaching 16 neonatal deaths per 1,000 live births in 2025. By 2030, the projected rate is estimated to reach 15 neonatal deaths per 1,000 live births—missing the target of 12 neonatal deaths per 1,000 live births.

Neonatal deaths per 1,000 live births



Legend

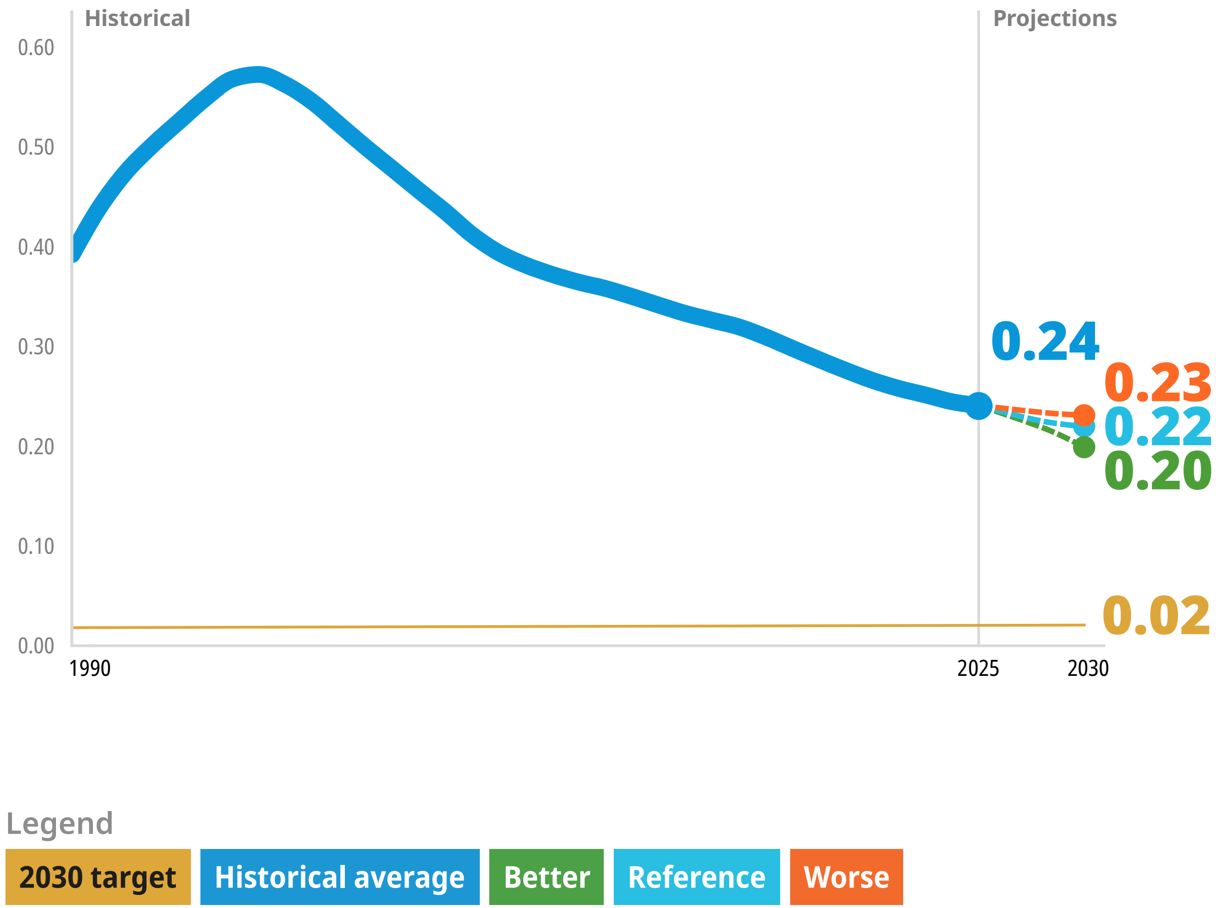
2030 target | Historical average | Better | Reference | Worse

HIV

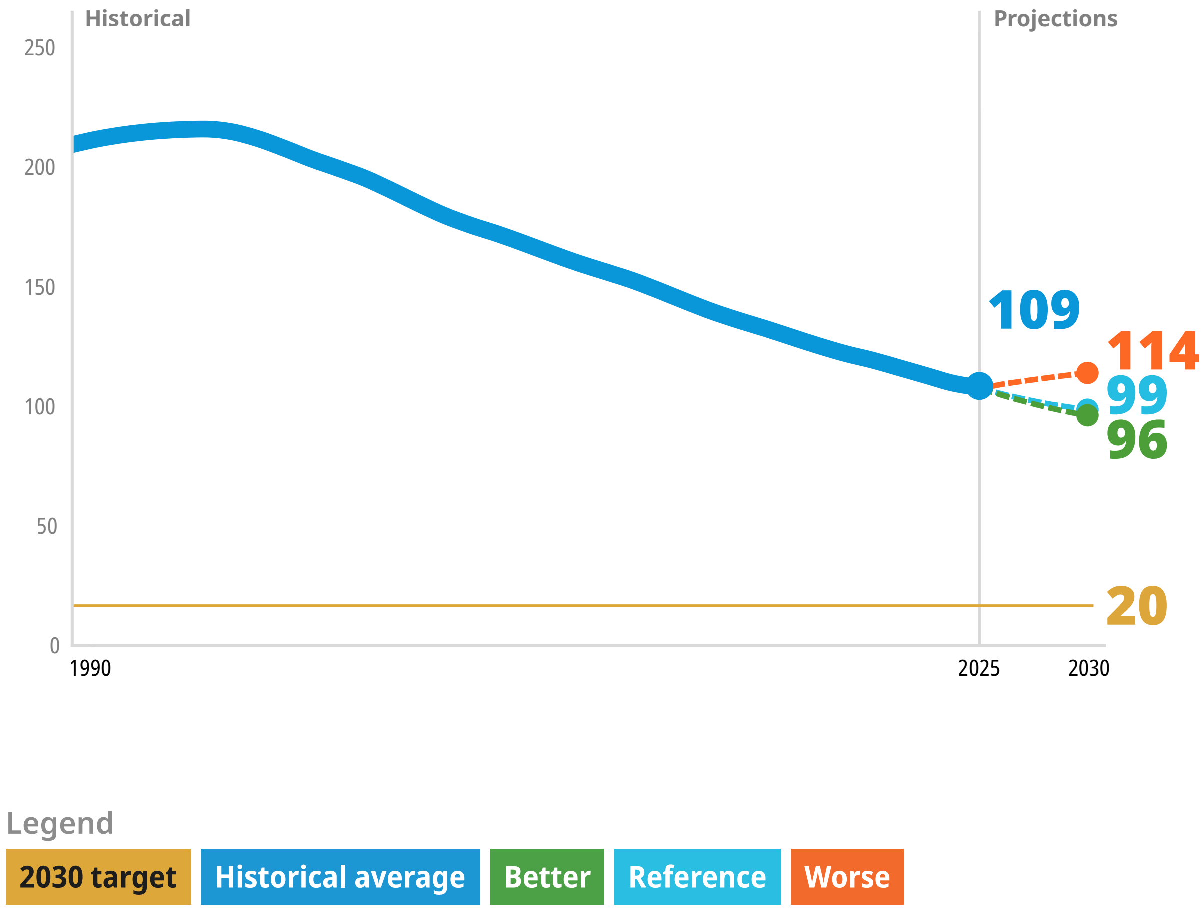
SDG TARGET 3.3
END THE EPIDEMICS OF AIDS, TUBERCULOSIS, MALARIA, AND NEGLECTED TROPICAL DISEASES AND COMBAT HEPATITIS, WATER-BORNE DISEASES, AND OTHER COMMUNICABLE DISEASES.

Globally, HIV incidence has declined steadily since its peak, reaching a low of 0.24 in 2025. However, recent disruptions to HIV funding and programming have slowed that trend, with incidence now projected to fall only to 0.22 per 1,000 people by 2030—more than 10 times the target of 0.02 per 1,000 people.

New cases of HIV per 1,000 people



New cases of tuberculosis per 100,000 people



TUBERCULOSIS

SDG TARGET 3.3
END THE EPIDEMICS OF AIDS, TUBERCULOSIS, MALARIA, AND NEGLECTED TROPICAL DISEASES AND COMBAT HEPATITIS, WATER-BORNE DISEASES, AND OTHER COMMUNICABLE DISEASES.

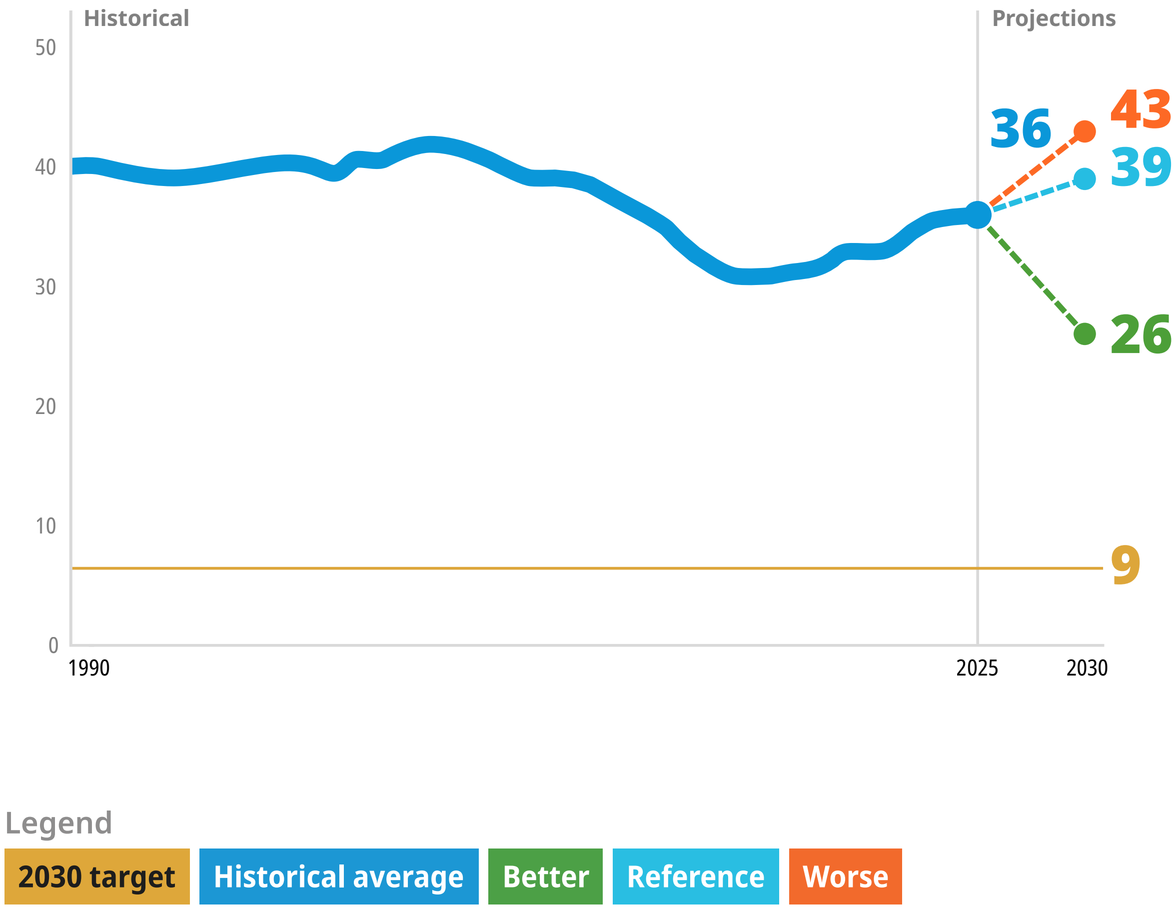
Globally, there were 109 new cases of tuberculosis per 100,000 people in 2025. The estimate indicates that there could be static progress from 2026, with new cases of tuberculosis reaching 99 per 100,000 people in 2030—that's nearly five times the target of 20 new cases per 100,000 people. However, as efforts to expand TB molecular testing reach more people, including those without symptoms, reported cases may increase in the near term—a sign of better detection, not worsening disease.

MALARIA

SDG TARGET 3.3
END THE EPIDEMICS OF AIDS, TUBERCULOSIS, MALARIA, AND NEGLECTED TROPICAL DISEASES AND COMBAT HEPATITIS, WATER-BORNE DISEASES, AND OTHER COMMUNICABLE DISEASES.

Progress on decreasing the number of new cases of malaria has stalled, reaching 36 cases per 1,000 people in 2025. The 2030 projection estimates that progress may reverse, with new cases increasing to 39 cases per 1,000 people by 2030.

New cases of malaria per 1,000 people

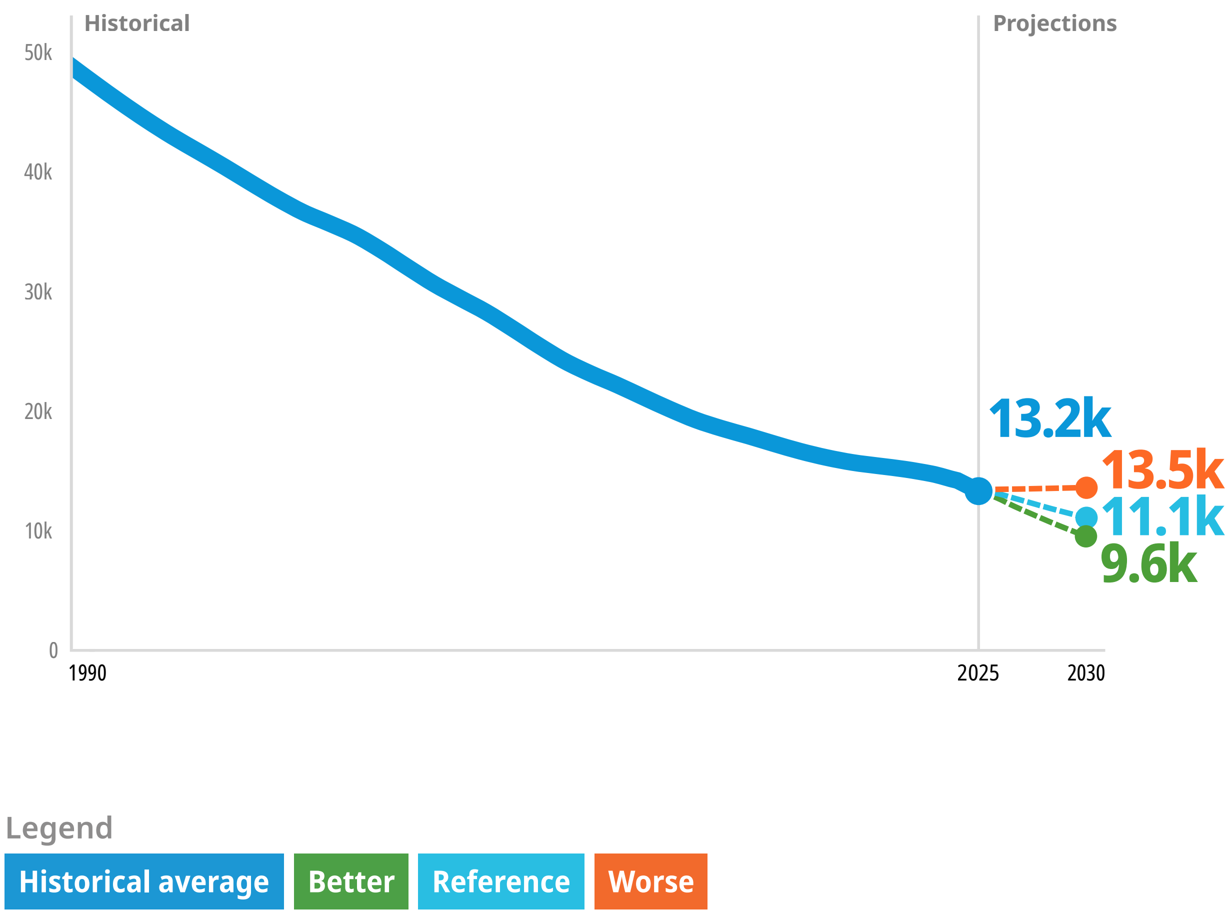


NEGLECTED TROPICAL DISEASES

SDG TARGET 3.3
END THE EPIDEMICS OF AIDS, TUBERCULOSIS, MALARIA, AND NEGLECTED TROPICAL DISEASES (NTDS) AND COMBAT HEPATITIS, WATER-BORNE DISEASES, AND OTHER COMMUNICABLE DISEASES.

For 15 NTDs, it is estimated that the total prevalence has declined globally in 2025 to 13,214 cases per 100,000. The prevalence of these 15 NTDs is projected to continue to decline to just over 11,000 per 100,000 by 2030.

Prevalence of 15 NTDs per 100,000 people

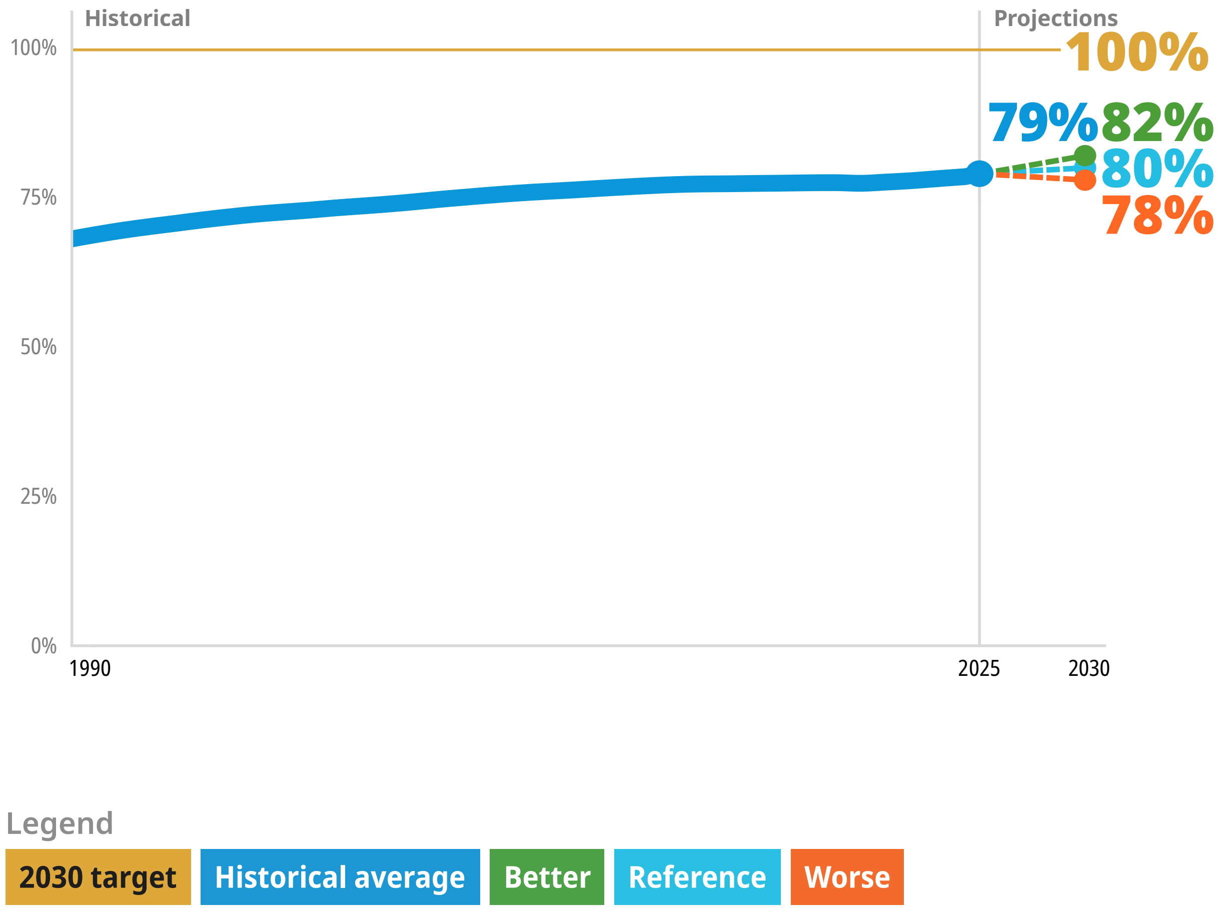


FAMILY PLANNING

SDG TARGET 3.7
ENSURE UNIVERSAL ACCESS TO SEXUAL AND REPRODUCTIVE HEALTH CARE SERVICES, INCLUDING THOSE FOR FAMILY PLANNING.

Globally, it is estimated that almost 8 out of 10 women who identified as having a need for contraception are using a modern method to achieve their reproductive goals. Projections suggest progress to meet their need will stall through 2030.

Percentage of women of reproductive age (15–49) who have their need for family planning satisfied with modern methods

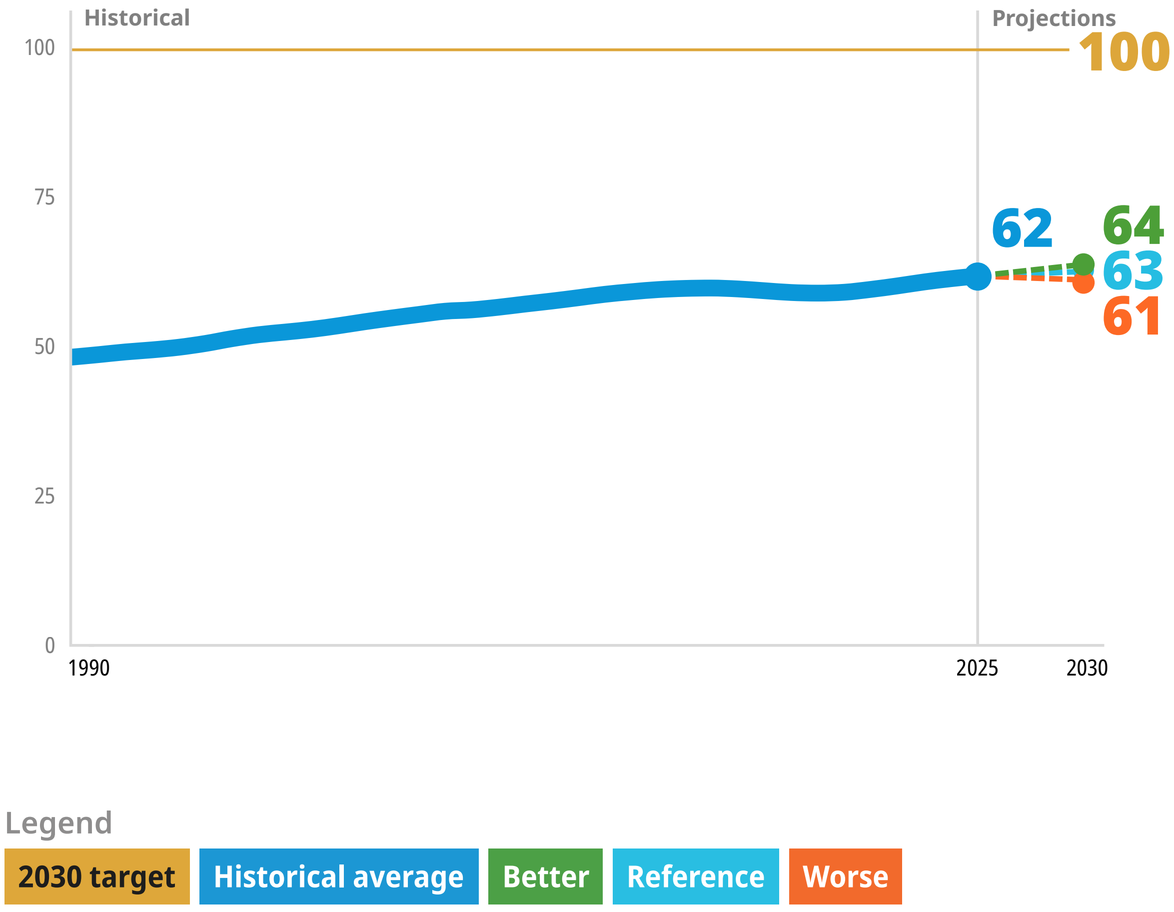


UNIVERSAL HEALTH COVERAGE

SDG TARGET 3.8
ACHIEVE UNIVERSAL HEALTH COVERAGE FOR ALL.

Coverage of essential health services is still recovering following pandemic reversals, increasing from an index score of 59 in 2020 to 62 in 2025. The score is estimated to increase slightly to 63 by 2030, indicating that more work is needed to ensure universal health coverage for all.

Performance score of the UHC effective coverage index



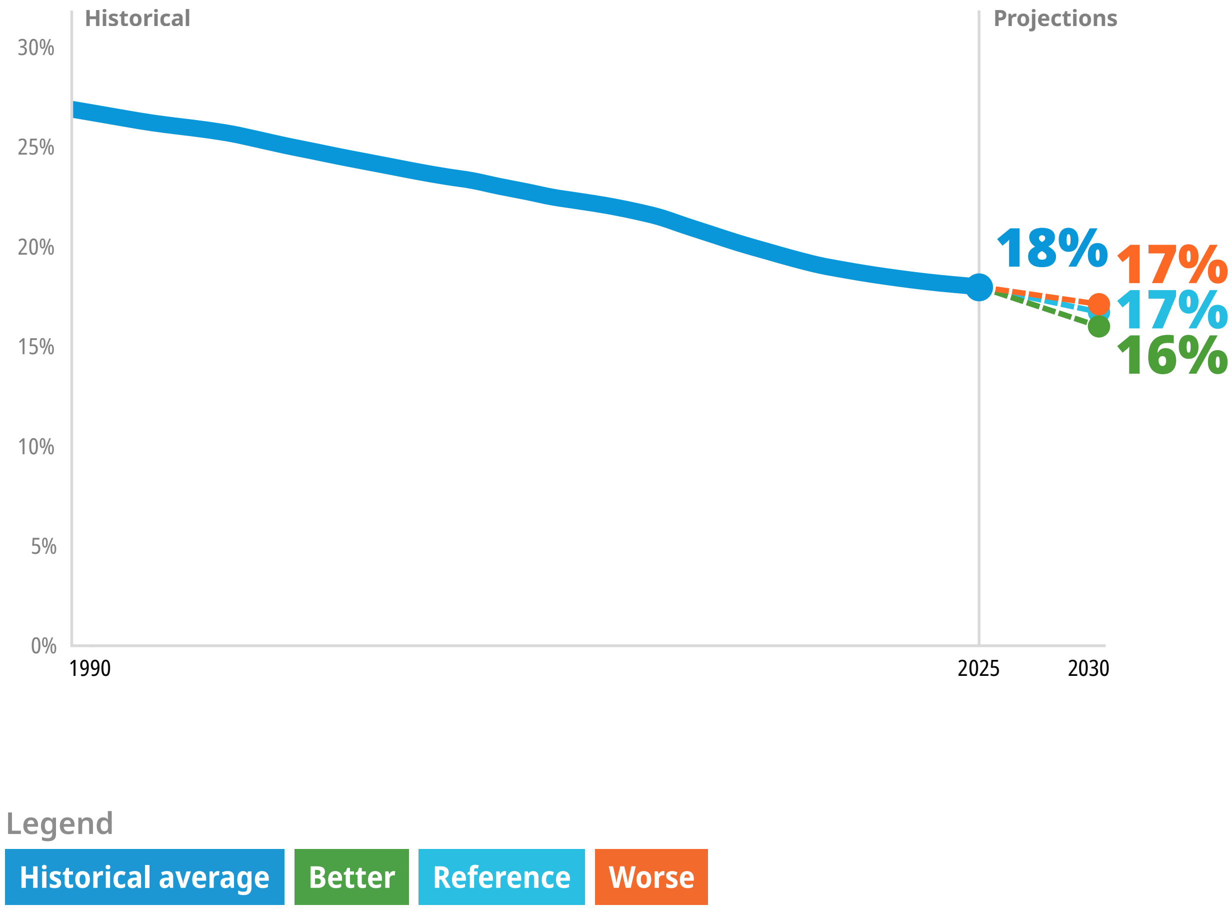
SMOKING

SDG TARGET 3.A
STRENGTHEN THE IMPLEMENTATION OF THE WORLD HEALTH ORGANIZATION FRAMEWORK CONVENTION ON TOBACCO CONTROL (FCTC) IN ALL COUNTRIES.

Globally, the percentage of people aged 15 and older who use any tobacco product has declined over the last decade, reaching 18% in 2025. Projections estimate further decline to 17% by 2030.

According to WHO's latest Global Tobacco Control Report, 6.1 billion people are now covered by at least one evidence-based policy from the FCTC, covering over 75% of the global population and representing a fivefold increase since 2007.

Age-standardized smoking prevalence among people ages 15 and older

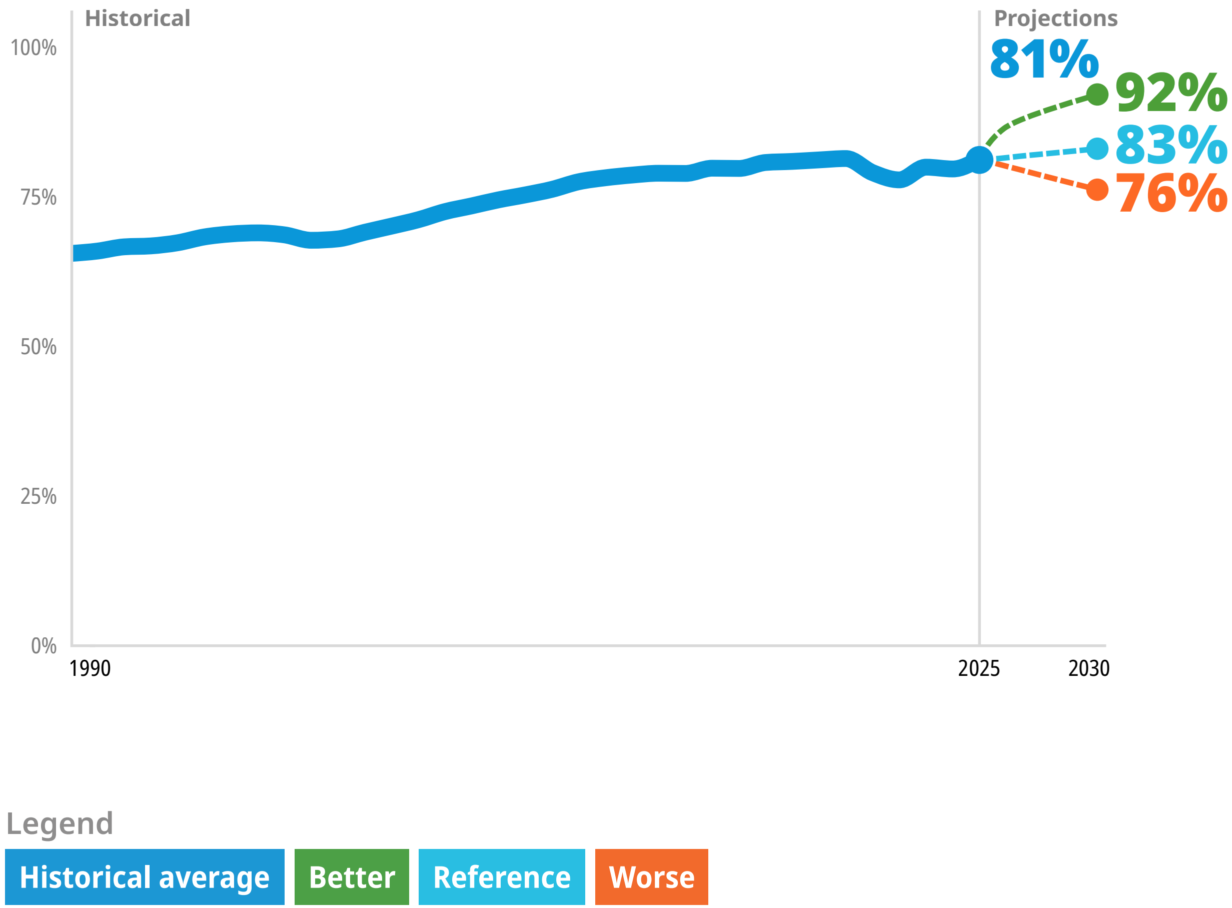


VACCINES

SDG TARGET 3.B
SUPPORT THE RESEARCH AND DEVELOPMENT OF VACCINES AND MEDICINES FOR THE COMMUNICABLE AND NONCOMMUNICABLE DISEASES THAT PRIMARILY AFFECT DEVELOPING COUNTRIES AND PROVIDE ACCESS TO AFFORDABLE ESSENTIAL MEDICINES AND VACCINES.

In 2025, the global estimate for diphtheria, tetanus, and pertussis (DTP) third-dose vaccine coverage is 81%. By 2030, DTP third-dose vaccine coverage is estimated to be 83%. Understanding the significant differences that exist at the subnational level is key to reaching the children who are still being missed.

Coverage of DTP (third dose)

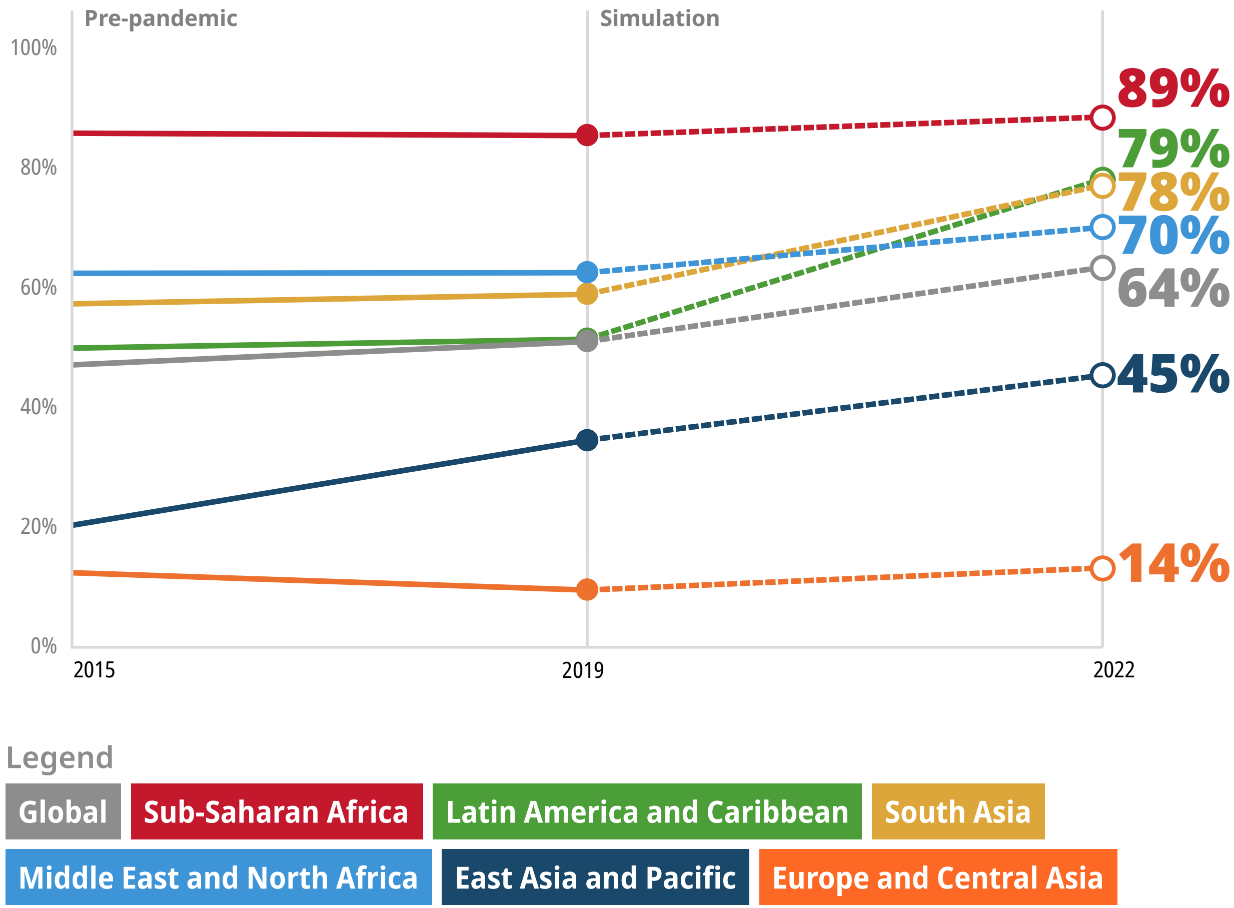


EDUCATION

SDG TARGET 4.1
ENSURE THAT ALL GIRLS AND BOYS COMPLETE FREE, EQUITABLE, AND QUALITY PRIMARY AND SECONDARY EDUCATION LEADING TO RELEVANT AND EFFECTIVE LEARNING OUTCOMES.

The latest simulations suggest that 70% of children in low- and middle-income countries are not able to read and understand a text by age 10, even if they are in school.

Proportion of children who cannot read and understand a simple text by age 10

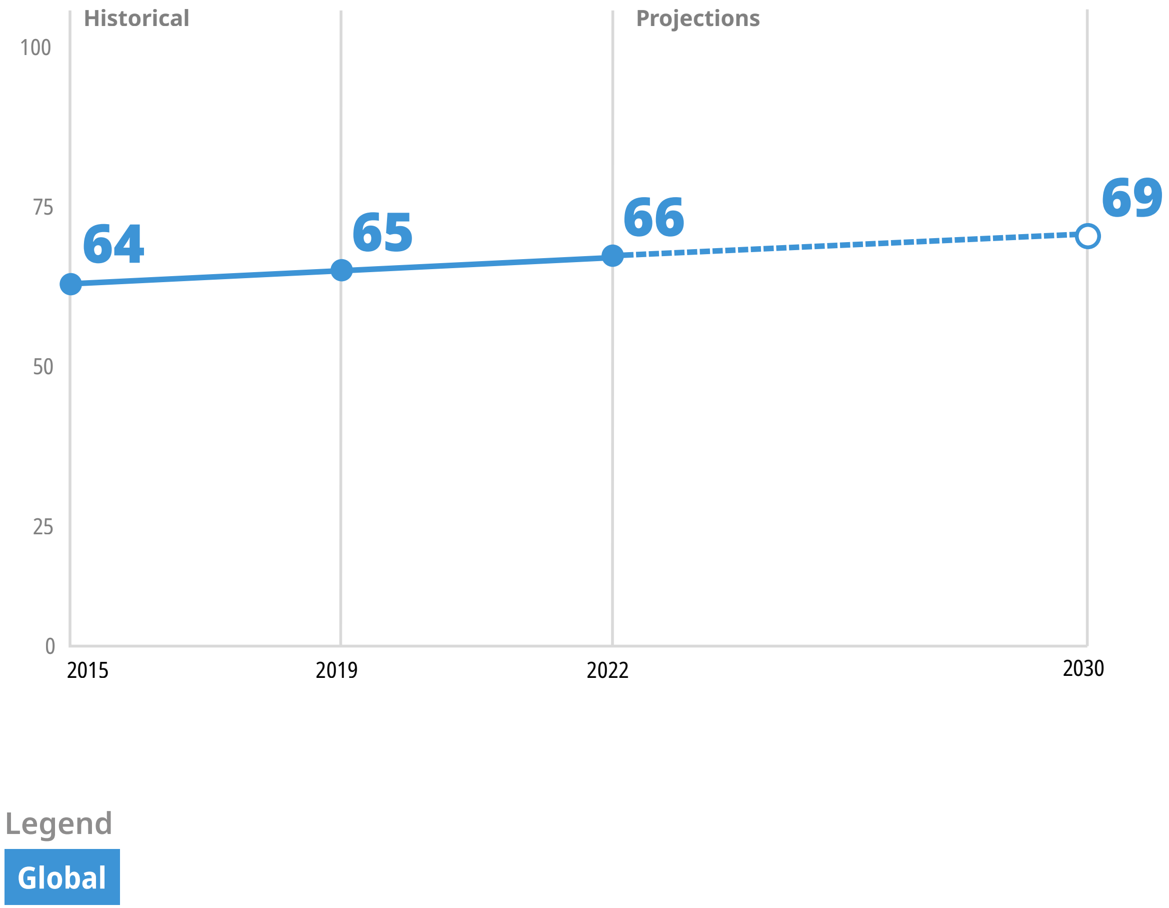


GENDER EQUALITY

SDG TARGET 5
ACHIEVE GENDER EQUALITY AND EMPOWER ALL WOMEN AND GIRLS.

Nearly three-quarters of the SDG targets—particularly those under SDG 1 (poverty), SDG 4 (education), SDG 5 (gender equality), and SDG 8 (decent work)—rely on gender equality. Yet no country is on track to achieve gender equality across the SDGs by 2030. If the current trends continue, global gender equality won't be achieved until the 22nd century.

SDG Gender Index score

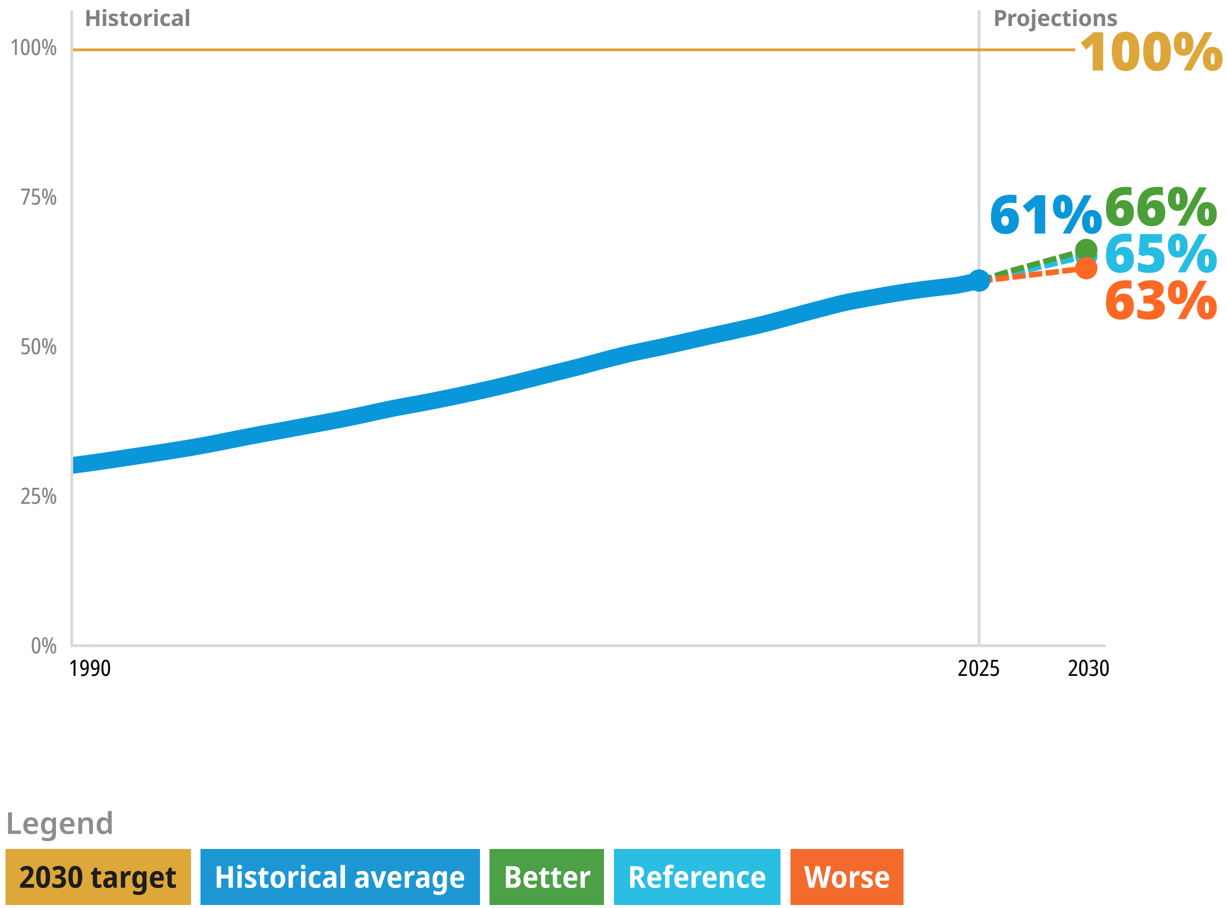


SANITATION

SDG TARGET 6.2
ACHIEVE ACCESS TO ADEQUATE AND EQUITABLE SANITATION AND HYGIENE FOR ALL AND END OPEN DEFECATION, PAYING SPECIAL ATTENTION TO THE NEEDS OF WOMEN AND GIRLS AND THOSE IN VULNERABLE SITUATIONS.

The proportion of the population using safely managed sanitation has been rising. In 2025, 61% of the global population were using safely managed sanitation. By 2030, it is estimated that progress will slowly increase to 65% of the global population—missing the target to ensure safe sanitation for all.

Proportion of population using safely managed sanitation



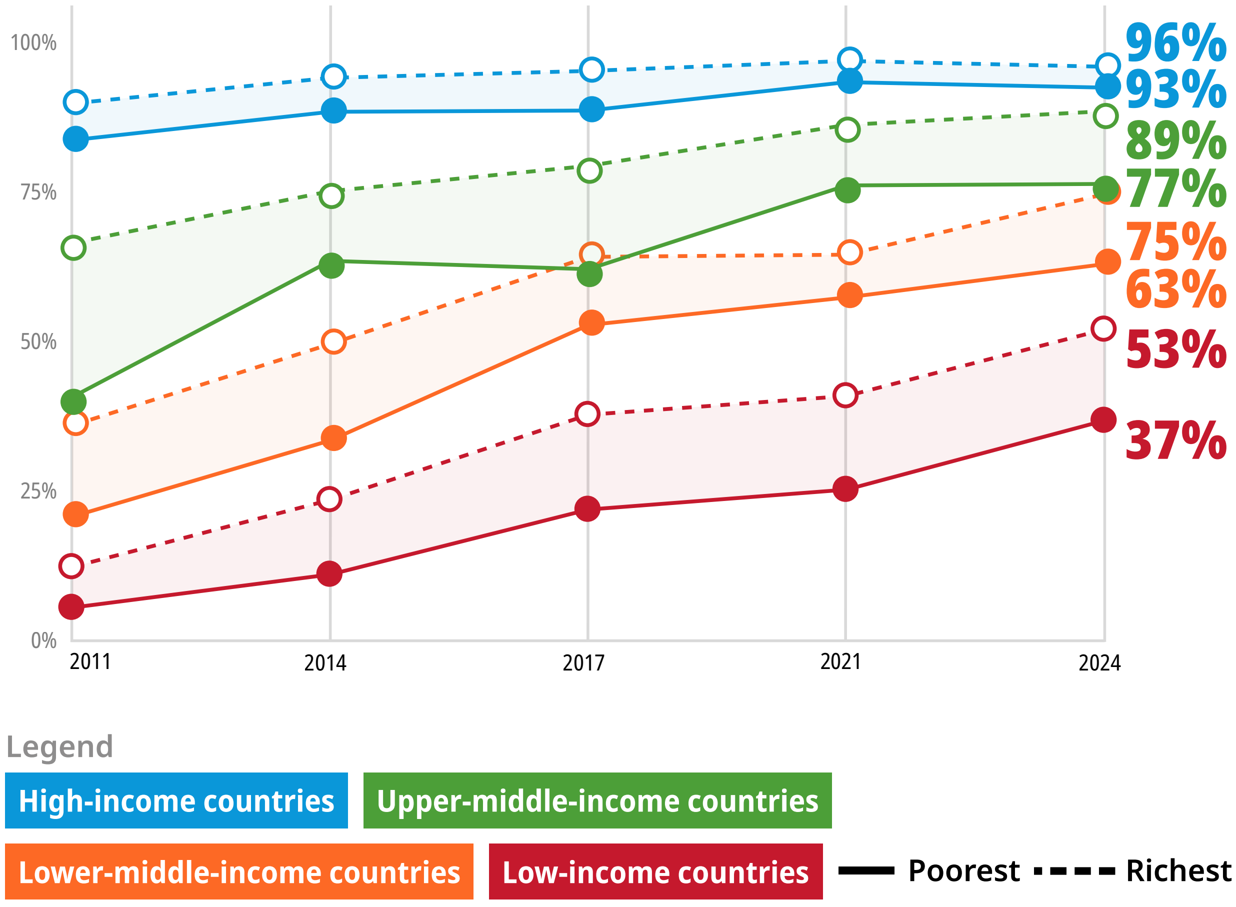
8 DECENT WORK AND ECONOMIC GROWTH

INCLUSIVE FINANCIAL SYSTEMS

SDG TARGET 8.10
STRENGTHEN THE CAPACITY OF DOMESTIC FINANCIAL INSTITUTIONS TO ENCOURAGE AND EXPAND ACCESS TO BANKING, INSURANCE, AND FINANCIAL SERVICES FOR ALL.

The world has made rapid progress in expanding financial inclusion. Globally, 79% of adults now own a financial account, up from 51% in 2011.

Percentage of adults (ages 15 and older) with an account at a bank or other financial institution or with a mobile-money service provider, poorest and richest



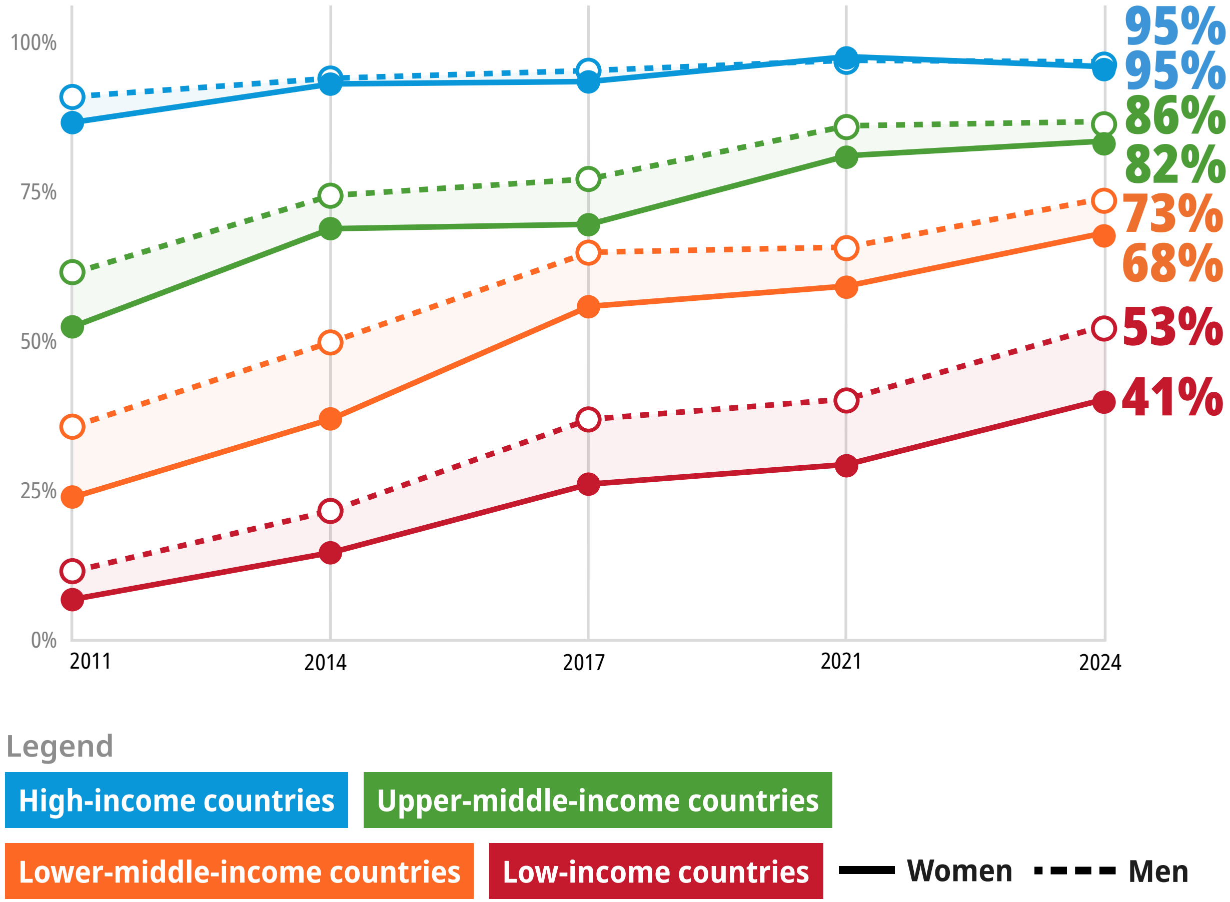
8 DECENT WORK AND ECONOMIC GROWTH

INCLUSIVE FINANCIAL SYSTEMS

SDG TARGET 8.10
STRENGTHEN THE CAPACITY OF DOMESTIC FINANCIAL INSTITUTIONS TO ENCOURAGE AND EXPAND ACCESS TO BANKING, INSURANCE, AND FINANCIAL SERVICES FOR ALL.

Most important, the gender gap in account ownership is also decreasing.

Percentage of adults (ages 15 and older) with an account at a bank or other financial institution or with a mobile-money service provider, women and men



2026 DATA SOURCES

The data sources for facts and figures featured in the 2026 Goalkeepers Report are listed here by section. Brief methodological notes are included for unpublished analyses. Full citations, links to source materials, and additional references can be found on the Goalkeepers website at gates.ly/2026GKDataSources.

This report was developed by Gates Foundation staff and partners. AI tools were used to support some of the editing process. All content was led, reviewed, and approved by human writers, designers, editors, data experts, and program staff.

INTRODUCTION

NOTHING HAS FELT LIKE THIS

AI Adoption Speed

AI tools have reached global scale faster than any technology in history. ChatGPT reached 100 million monthly active users within approximately two months of its launch in late 2022, compared to approximately nine months for TikTok and two and a half years for Instagram. Earlier technologies spread more slowly still: it took decades for the personal computer to reach comparable levels of household penetration in the United States.

Hu, K. “ChatGPT Sets Record for Fastest-Growing User Base—analyst note,” Reuters, February 2, 2023. www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01.

Meta Platforms, Inc., SEC filings and historical company reporting, (2004–2008), Facebook user growth records. Facebook reached 100 million users in 2008, approximately four and a half years after its February 2004 launch.

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U.S. Department of Commerce. *“The Emerging Digital Economy.”* Washington, DC. 1998. www.cga.ct.gov/PS99/rpt%5Colr%5Chtm/99-R-0047.htm

GBD 2023 Causes of Death Collaborators. “Global Burden of 292 Causes of Death in 204 Countries and Territories and 660 Subnational Locations, 1990–2023: A Systematic Analysis for the Global Burden of Disease Study 2023.” The Lancet 406, no. 10513 (2025): 1811-1872. www.thelancet.com/journals/lancet/article/PIIS0140-6736(25)01637-X/fulltext.

United Nations Inter-agency Group for Child Mortality Estimation (UN IGME). *Levels and Trends in Child Mortality 2025*. March 2026. data.unicef.org/resources/levels-and-trends-in-child-mortality-2025/.

World Bank. *Poverty and Inequality Platform*. Version 20260324_2021. Data set. World Bank Group, 2025. pip.worldbank.org/.

Institute for Health Metrics and Evaluation (IHME). *Financing Global Health 2025: Cuts in Aid and Future Outlook*. Seattle, Washington. IHME, 2025. www.healthdata.org/research-analysis/library/financing-global-health-2025-cuts-aid-and-future-outlook

Apeagyei, A. E., Bisignano, C., Elliott, H., Hay, S.I., Lidral-Porter, B., Nam, S., Shyong, C., Tsakalos, G., Zlavog, B., Barış, E., Murray, C.J.L., and Dieleman, J.L. “Tracking Development Assistance for Health, 1990–2030: Historical Trends, Recent Cuts, and Outlook.” *The Lancet* 406, no. 10501 (2025): 337–348. doi.org/10.1016/S0140-6736(25)01240-1

EXPLORE THE DATA

WE'VE MADE PROGRESS. BUT IF CURRENT TRENDS PERSIST, SO DOES INEQUALITY.

Institute for Health Metrics and Evaluation, (July 2026). [Custom analysis. Full methodology is detailed below].

Friedman, J., York H, Graetz N., et al. “Measuring and Forecasting Progress towards the Education-Related SDG Targets.” Nature 580, 636-639 (2020). doi.org/10.1038/s41586-020-2198-8

Institute for Health Metrics and Evaluation, (July 2026). [Custom analysis. Full methodology is detailed below].

Institute for Health Metrics and Evaluation, (July 2026). [Custom analysis. Full methodology is detailed below].

The data visualizations in this report are representations of the data. Full datasets are available upon request.

IMPACT

WHERE THE DIFFERENCE GETS MADE: A NURSE, A FARMER, A TEACHER

Institute for Health Metrics and Evaluation, (July 2026). [Custom analysis. Full methodology is detailed below].

In addition to the custom analysis, there is published research on the health workforce challenges in sub-Saharan Africa, including:

Ahmat, A., et al. "The Health Workforce Status in the WHO African Region: Findings of a Cross-Sectional Study." *BMJ Global Health 7*, suppl. 1 (2022). pmc.ncbi.nlm.nih.gov/articles/PMC9109011/

GBD 2019 Human Resources for Health Collaborators. "Measuring the Availability of Human Resources for Health and Its Relationship to Universal Health Coverage for 204 Countries and Territories from 1990 to 2019: A Systematic Analysis for the Global Burden of Disease Study 2019." *The Lancet* 399, no. 10341 (2022): 2129–2154. doi.org/10.1016/S0140-6736(22)00532-3

CALL TO ACTION

FIRST, AI TOOLS HAVE TO WORK IN EVERY LANGUAGE PEOPLE SPEAK.

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, et al. "Language Models are Few-Shot Learners." *Advances in Neural Information Processing Systems*, 33 (2020): 1877–1901. arxiv.org/abs/2005.14165

Wang, W., Tu, Z., Chen, C., Yuan, Y., Huang, J., Jiao, W., and Lyu, M. "All Languages Matter: On the Multilingual Safety of LLMs." *In Findings of the Association for Computational Linguistics: ACL 2024*, 5865–5877. Bangkok, Thailand: Association for Computational Linguistics, 2024. aclanthology.org/2024.findings-acl.349/

Martínez, G., Conde, J., Merino-Gómez, E., Bermúdez-Margaretto, B., Hernández, J. A., Reviriego, P., and Brysbaert, M. "Establishing Vocabulary Tests as a Benchmark for Evaluating Large Language Models. PLOS ONE, 19, no. 12(2024): e0308259. doi.org/10.1371/journal.pone.0308259

Liu, Y., Huang, J., and Wang, H. *Who on Earth is Using Generative AI? Global Trends and Shifts in 2025*. Policy Research Working Paper 11231. Washington, DC: World Bank, 2025. openknowledge.worldbank.org/bitstreams/c5a7eb99-17c5-4d0e-a5ce-3d9fcfe184a7/download

Microsoft AI Economy Institute. *Global AI Diffusion Report: 2025* H2. Microsoft, 2026. www.microsoft.com/en-us/research/wp-content/uploads/2026/01/Microsoft-AI-Diffusion-Report-2025-H2.pdf

The "one billion" and "7 billion" figures are illustrative, not precise measurements. The cited sources (World Bank, 2025; Microsoft AI Economy Institute, 2026) document a large and widening AI access gap by income and region.

Olatunji, T., Afonja, T., Yadavalli, A., Emezue, C.C., Singh, S., Dossou, B.F.P., Osuchukwu, J., Osei, S., Tonja, A.L., Etori, N., Mabataku, C. "AfriSpeech-200: Pan-African accented speech dataset for clinical and general domain ASR." *Transactions of the Association for Computational Linguistics*, 11 (2023): 1669–1685. doi.org/10.1162/tacl_a_00627

GUEST ESSAYS

EARLY EVIDENCE SHOWS WHAT'S POSSIBLE.

The four examples from Kenya, Sierra Leone, the United States, and India were selected because they represent early evidence of what becomes possible when AI tools are built for frontline workers. They are not the only tools showing promise in these sectors. Many others exist.

The Gates Foundation has provided support to Penda Health, Kiddom, MahaVistaar, and to Fab AI the implementing partner for the Gemini Guided Learning trial in Sierra Leone.

Korom, R., Kiptinness, S., Adan, N., Said, K., Ithuli, C., Rotich, O., Kimani, B., King'ori, I., Kamau, S., Atemba, E., Aden, M., Bowman, P., Sharman, M., Soskin Hicks, R., Distler, R., Heidecke, J., Arora, R. K., and Singhal, K. "AI-Based Clinical Decision Support for Primary Care: A Real-World Study." arXiv preprint, 2025. arxiv.org/abs/2507.16947

OpenAI. "Pioneering an AI Clinical Copilot with Penda Health." July 22, 2025. www.openai.com/index/ai-clinical-copilot-penda-health.

Ghahramani, Z. "Measuring the Impact of Learning with AI in Sierra Leone and Beyond." Google DeepMind / Fab AI, June 9, 2026. deepmind.google/blog/measuring-the-impact-of-learning-with-ai-in-sierra-leone-and-beyond/.

Manjee, A. "In NYC District, Technology Works With Pencil and Paper to Help Kids Learn Math," *The 74*, July 9, 2026. www.the74million.org/article/in-nyc-district-technology-works-with-pencil-and-paper-to-help-kids-learn-math. Note: Author is co-founder of Kiddom.

Kiddom. "Kiddom Launches Atlas, the First AI-Powered Instructional Technology Layered on High-Quality Instructional Materials," *BusinessWire*, February 23, 2026. www.businesswire.com/news/home/20260220676382/en/Kiddom-Launches-Atlas-the-First-AI-Powered-Instructional-Technology-Layered-on-High-Quality-Instructional-Materials.

Government of Maharashtra / OpenAgriNet (2025), *MahaVISTAAR Program Monitoring Data* [program monitoring data; available at: maharashtra.gov.in/ or upon request from Maharashtra Agriculture Department, India].

MahaVISTAAR launched through the Maharashtra state government's agricultural digital infrastructure. Cost per farmer figure reflects government operational costs per active user as of late 2025.

METHODOLOGY FOR 2026 GOALKEEPERS CUSTOM ANALYSIS

WE'VE MADE PROGRESS. BUT IF CURRENT TRENDS PERSIST, SO DOES INEQUALITY.

Educational attainment

The schooling gap estimate draws on educational attainment by age cohort and region, modeled using the framework described in Friedman et al., 2020, which models within-country distributions of years of schooling, from which mean years of educational attainment is calculated.

To produce forecasts, for each country, we forecast the mean years of schooling (MYS) within ages 25 to 29 by modeling the year-to-year change in MYS as a function of the MYS level. When a location's rate of change in 2023 was substantially faster or slower than the model prediction, we allowed the rate of change to gradually approach the predicted value over time before following the model's assumed dynamics. Forecasts of educational attainment in other age groups were then estimated based on forecasts for ages 25 to 29.

Reference:

Friedman, J., York, H, Graetz, N., et al. "Measuring and Forecasting Progress towards the Education-Related SDG Targets." *Nature*. 580, 636-639 (2020). doi.org/10.1038/s41586-020-2198-8

Extreme poverty

The Institute for Health Metrics and Evaluation (IHME) estimates the extreme poverty rate as the proportion of the population living below a consumption level of $US3.00 per person per day in 2021 purchasing power parity-adjusted dollars, following the World Bank's current extreme poverty line definition.

Drawing on the methods described in Moses et al 2021, we estimated national mean consumption and the national consumption Lorenz curve. We first extracted household consumption and income data from various survey sources, cleaned and standardized the data, and cross-walked income data to consumption using a linear mixed effects model. We then modeled a complete series of estimates across 204 countries for the years 1980 to 2023, generating 500 draws to incorporate uncertainty. We combined the mean consumption and Lorenz curve estimates to generate the consumption distribution for each country, year, and population percentile. From these consumption distributions, we extracted the percentage of the population living on less than $US3.00 per day to obtain estimates of the national extreme poverty rate.

National extreme poverty rates were forecasted from 2024 to 2045. We first fit a meta-stochastic frontier model to historical consumption and poverty estimates, extracted the modeled inefficiency from the most recent observed year, and held it constant by country over 2024 to 2045. Consumption was forecast from 2023 to 2045 using a linear mixed effects model with IHME GDP per capita forecasts as a predictor and country-level random effects. We then applied the frontier model to the forecast levels of inefficiency and consumption for each country and year to produce the national extreme poverty rate forecasts.

Reference:

Moses, M. W., Kharas, H., Miller-Petrie, M. K., Tsakalos, G., Marczak, L., Hay, S. I., Murray, C. J. L., and Dieleman, J. L. *Global Poverty and Inequality from 1980 to the COVID-19 Pandemic*. SocArXiv, March 18, 2021. https://osf.io/preprints/socarxiv/x47np_v1

WHERE THE DIFFERENCE GETS MADE: A NURSE, A FARMER, A TEACHER

Physician density

The health workforce estimates are based on forecasted physician density per capita, using data from Knight et al, 2026. Estimates were produced for 204 countries and territories from 1990 to 2023, and forecasts to 2045 were produced from an ensemble model driven by historical rates of change with varying weights across child models for weighting recent years more heavily, informed by out-of-sample predictive validity.

Reference:

Knight, M., Haakenstad, A., & GBD 2023 Collaborators. (2026, July). "Measuring the composition and availability of human resources for health by sex in 204 countries and territories, 1990–2023, and workforce gaps for universal health coverage: A systematic analysis for the Global Burden of Disease Study 2023." *The Lancet*. www.thelancet.com/journals/lanpub/article/PIIS2468-2667(26)00145-3/fulltext

SDG INDICATORS
IHME METHODOLOGY

Measuring the impact of foreign aid cuts on SDG indicators

To estimate the impact of recent aid cuts, there are two primary areas of work that IHME undertook: 1) modeling and estimating the impact of funding cuts across all relevant sources on projections of development assistance for health (DAH) and total health spending (THE); and 2) estimating the associated impact that reductions in health spending will have on the Goalkeepers Sustainable Development Goal (SDG) indicators.

To comprehensively measure funding cuts both domestically and internationally to foreign aid, IHME collected and standardized estimates of global health spending from diverse data sources, including commitments and disbursements from development project records, annual budgets, financial statements, and revenue reports. Long-term forecasts through 2050 for DAH were generated using donor targets, historical trends, and GDP-based forecasting, while future THE was predicted through ensemble models assessing key indicators like government expenditure and out-of-pocket costs. IHME's estimates and forecasts of foreign aid are based on publicly available data as of July 15, 2026. Detailed methodologies are available in the online Methods Annex of the 2025 Financing Global Health report www.healthdata.org/research-analysis/library/financing-global-health-2025-cuts-aid-and-future-outlook.

To quantify the impact of reductions in development aid on the SDG indicators, IHME analyzed the relationship between each indicator and historical health spending. We used a nonparametric stochastic frontier analysis approach, where the "frontier" represents the best possible outcome (e.g., the lowest number of new tuberculosis cases) for a given level of health spending. The model assumes that this efficiency persists into the future, allowing us to calculate the marginal cost, in decreased health coverage, lives lost, or additional cases, of reduced funding.

For each SDG indicator reported, apart from smoking prevalence and HIV incidence, forecasts were produced using spending trajectories derived from the best available country-level expenditure estimates. For 2025, these estimates capture observed funding cuts; from 2026 onward, they reflect country-specific projections rather than a fixed percentage reduction. We leveraged donor countries' official development assistance (ODA) per gross national income (GNI) targets where available and otherwise applied projected growth rates of ODA per GNI based on a linear regression model and expected changes in GDP per capita. Details for how we captured the impacts of funding on HIV are described in the indicator section below.

Reference:

Apeagyei, A., Barış, E., Dieleman, J., Elliott, H., Leach-Kemon, K., Lidral-Porter, B., Murray, C. J. L., Nam, S., Shyong, C., Tsakalos, G., and Zlavog, B. *Financing Global Health 2025: Cuts in Aid and Future Outlook—Methods Annex*. Seattle, Washington, Institute for Health Metrics and Evaluation, 2025. www.healthdata.org/research-analysis/library/financing-global-health-2025-cuts-aid-and-future-outlook

INDICATORS ESTIMATED BY IHME

IHME produced estimates and forecasts for 13 of the SDG indicators included in the 2026 Goalkeepers Report. The section below provides details on how each indicator is estimated.

Stunting

IHME measures child stunting prevalence as height-for-age more than two standard deviations below the reference median on the height-age growth curve based on WHO 2006 growth standards for children 0 to 59 months.

The modeling uses a combination of mean height-for-age z-scores (HAZ) and severity-specific stunting prevalences (mild, moderate, severe, and extreme) to estimate the entire distribution of HAZ for each location, sex, and year for each of six distinct age groups of children <5. Each continuous distribution was integrated to produce the final stunting prevalence estimate.

Our forecasts of stunting are driven by several factors: historic temporal patterns, household consumption, the sociodemographic index and climate change. To generate forecasts of stunting that incorporate the effect of climate change, we analyzed individual-level geolocated data from the Demographic and Health Surveys (DHS) to determine the relationship between the prevalence of stunting and climate factors. We utilized data totaling over 1.1 million geo-located child observations from 145 surveys, covering 57 countries. We implemented a statistical model that estimated the relationship between stunting prevalence and climate factors (mean annual temperature and days over 30°C) while controlling for altitude, household consumption and country-level random effects. We also include an interaction term between household consumption and days over 30°C to capture the mitigating factor of increasing household consumption on heat stress. In addition to the climate-specific portion of the projection, we also model any remaining or residual variation between the predictions and the historical GBD estimates using the sociodemographic index (SDI) as a predictor of the residuals. The better and worse scenarios were produced by taking the 85th and 15th percentile rates of change observed across location-years in the past and applying those rates of change to all locations in the future.

To estimate the impact of reduced development assistance for health, we used a nonparametric stochastic frontier approach (as detailed in the “Measuring funding cuts to foreign aid and their impact on SDGs” section above) to model how decreased spending—accounting for total health spending including World Food Programme assistance and varying by country and year—would impact stunting prevalence and adjusted our forecasts per the reference scenario for each country through 2045 accordingly.

Under-5 mortality rate

IHME defines the under-5 mortality rate as the probability of death between birth and age 5. It is expressed as the number of deaths per 1,000 live births.

Estimates used all available data from vital registration, sample registration, surveys, and censuses, which were modeled via a statistical model for age-specific mortality rates that incorporates both parametric and non-parametric methods. Age-specific mortality rates for ages 0 to 6 days, 7 to 27 days, 1 to 5 months, 6 to 11 months, 1 to 2 years, and 2 to 4 years were jointly estimated in the model, then converted to the under-5 mortality rate.

Forecasts to 2045 use the modeling approach published in GBD 2021 Forecasting Collaborators, based on a combination of key drivers, including Global Burden of Disease (GBD) risk factors linked to individual causes of death in the under-5 age group (e.g. child stunting, wasting, and underweight), selected interventions (e.g., vaccines), and SDI. Forecasts are produced for each cause of death and are then aggregated to all-cause mortality, which are then used to compute the final indicator.

Better and worse scenarios were constructed by applying the 85th and 15th percentile of historically observed rates of change to all drivers (risk factors, sociodemographic index, and interventions) across location-years, respectively.

To estimate the impact of reduced development assistance for health, we used a nonparametric stochastic frontier approach (as detailed in the “Measuring funding cuts to foreign aid and their impact on SDGs” section above) to model how decreased spending—varying by country and year—would increase under-5 mortality, and adjusted our forecasts per the reference scenario for each country through 2045 accordingly.

References:

GBD 2021 Forecasting Collaborators. (2024). “Burden of disease scenarios for 204 countries and territories, 2022–2050: A forecasting analysis for the Global Burden of Disease Study 2021.” *The Lancet*, 403 (10440), 2204–2256. doi.org/10.1016/S0140-6736(24)00685-8

Neonatal mortality rate

IHME defines neonatal mortality rate as the probability of death in the first 28 completed days of life. It is expressed as the number of deaths per 1,000 live births. Estimates used all available data from vital registration, sample registration, surveys, and censuses, which were modeled via a statistical model for age-specific mortality rates that incorporates both parametric and non-parametric methods. Age-specific mortality rates for ages 0-6 days and 7-27 days were jointly estimated in the model, then converted to neonatal mortality rate.

Forecasts to 2045 use the modeling approach published in GBD 2021 Forecasting Collaborators, based on a combination of key drivers, including Global Burden of Disease (GBD) risk factors linked to individual causes of death in the under-5 age group (e.g. child stunting, wasting, and underweight), selected interventions (e.g., vaccines), and SDI. Forecasts are produced for each cause of death and are then aggregated to all-cause mortality which are then used to compute the final indicator. Better and worse scenarios were constructed by applying the 85th and 15th percentile of historically observed rates of change to all drivers (risk factors, sociodemographic index and interventions) across location-years, respectively.

To estimate the impact of reduced development assistance for health, we used a nonparametric stochastic frontier approach (as detailed in the “Measuring funding cuts to foreign aid and their impact on SDGs” section above) to model how decreased spending—varying by country and year—would increase neonatal mortality, and adjusted our forecasts per the reference scenario for each country through 2045 accordingly.

References:

GBD 2021 Forecasting Collaborators. (2024). “Burden of disease scenarios for 204 countries and territories, 2022–2050: A forecasting analysis for the Global Burden of Disease Study 2021.” *The Lancet*, 403(10440), 2204–2256. doi.org/10.1016/S0140-6736(24)00685-8

HIV

IHME estimates the HIV rate as new HIV infections per 1,000 population. Estimation of HIV incidence employs two primary modeling packages: A GBD-adapted Estimation and Projection Package Age-Sex Model (EPP-ASM) for countries with robust HIV prevalence data from antenatal care clinics or representative population-based seroprevalence surveys; and a GBD-adapted Spectrum framework for the remaining locations. Forecasts are based on forecasted antiretroviral therapy (ART), prevention of mother-to-child transmission (PMTCT) coverage, and transmission rate. ART coverage data leverages nationally reported ART coverage program data, and for Goalkeepers 2025 for the year 2025 for sub-Saharan Africa adult ART coverage data came from the UNAIDS 2026 data release. Updates to this year's estimates and forecasts reflect newly integrated data for ART, updated household survey and antenatal care prevalence data, as well as refreshed input parameters reflecting the latest evidence on HIV mortality and disease progression.

Tuberculosis

IHME estimates new and relapse tuberculosis (TB) cases diagnosed within a given calendar year (incidence) using data from prevalence surveys, case notifications, and cause-specific mortality estimates as inputs to a statistical model that enforces internal consistency among the estimates.

IHME estimates incidence differently between countries with high-quality cause of death data and those without. For countries with high-quality data, we build incidence directly from age and sex-specific case notifications, combining all new and relapse cases. For countries with weaker systems, where notifications are less reliable, we instead model incidence from the relationship between TB mortality and incidence using the high-quality countries as a training set. We estimate mortality to incidence ratios as a function of age, sex, region and country specific summary measure of Healthcare Access Quality and then combine those ratios with our TB mortality estimates to derive incidence. All inputs are reconciled in a Bayesian disease model that estimates incidence, prevalence, remission, and mortality together and keeps them mutually consistent. An adjustment to align modeled incidence with reported notifications while accounting for the fact that not every notified case is true TB. Drawing on high-quality countries, we estimate the fraction of notified cases likely to be true (bacteriologically confirmed) cases and apply this to lower quality settings, correcting the overestimation that results from treating all notifications as true cases.

Forecasts to 2045 used an ensemble model driven by historical rates of change with varying weights across child models for weighting recent years more heavily, informed by out-of-sample predictive validity. Better and worse scenarios were constructed by applying the 85th and 15th percentile of historically observed rates of change across location-years, respectively.

To estimate the impact of reduced development assistance for health, we used a nonparametric stochastic frontier approach (as detailed in the "Measuring funding cuts to foreign aid and their impact on SDGs" section above) to model how decreased spending—varying by country and year—would increase TB incidence, and adjusted our forecasts per the reference scenario for each country through 2045 accordingly.

References:

Ledesma et al. "Global, Regional, and National Burden of Tuberculosis and Multidrug-Resistant Tuberculosis by HIV Status, 1990–2023: A Systematic Analysis for the Global Burden of Disease Study 2023." *The Lancet* Infectious Diseases. Forthcoming 2026. Supplementary appendix.

Ledesma et al. "Global, Regional, and National Age-Specific Progress towards the 2020 Milestones of the WHO End TB Strategy: A Systematic Analysis for the Global Burden of Disease Study 2021." *The Lancet* Infectious Diseases, 24, no. 7 (2024): 698-725. www.thelancet.com/journals/laninf/article/PIIS1473-3099(24)00007-0/fulltext

Ledesma et al. "Global-, Regional-, and National-Level Impacts of the COVID-19 Pandemic on Tuberculosis Diagnoses, 2020–2021." *Microorganism*s 11, no. 9 (2023): 2191. www.mdpi.com/2076-2607/11/9/2191

Malaria

IHME estimates the malaria rate as the number of new cases per 1,000 population. Malaria incidence estimates utilize data inputs from routine malaria case reports from national routine surveillance systems; cross-sectional, geolocated, and community-representative observations of Plasmodium falciparum parasite rate (PfPR); data on Plasmodium knowlesi specifically for Malaysia; data from the Multiple Indicator Cluster Survey (MICS) and Demographic and Health Survey for the estimation of treatment seeking; estimates of malaria interventions such as insecticide-treated bednets, indoor residual spraying, and effective treatment with an antimalarial drug; and other environmental, sociodemographic, and economic covariates.

Forecasts to 2045 were produced with a five-component model, all fit at the second administrative level: Model 1: modeling Plasmodium falciparum prevalence in 2 to 10 year olds (Pfpr2-10); Model 2: modeling the all-age prevalence-case rate given PfPR2-10; Model 3: modeling the age- and sex-specific case rate given all-age case rate; Model 4: modeling the all-age prevalence-fatality rate given PfPR2-10; and finally Model 5: modeling the age- and sex-specific fatality rate given the all-age fatality rate. Each model used Admin 2-level data from 2000 to 2025 on both the malaria outcomes but also the weighted fraction of the year where temperature is suitable for transmission (weighted by a continuous measure of suitability, ranging from 0 to 1 as a non-linear function of temperature), yearly flood days per capita, GDP per capita, and DAH spending on malaria (which captured any observed and forecasted spending cuts). The better and worse scenarios were produced by taking the 85th and 15th percentile rates of change observed across location-years in the past and applying those rates of change to all locations in the future.

Neglected tropical diseases

IHME measures the sum of the prevalence of 15 NTDs per 100,000 that are currently measured in the annual Global Burden of Disease study: human African trypanosomiasis, Chagas disease, cystic echinococcosis, cysticercosis, dengue, food-borne trematodiases, Guinea worm, soil-transmitted helminths (STH, comprising hookworm, trichuriasis, and ascariasis), leishmaniasis, leprosy, lymphatic filariasis, onchocerciasis, rabies, schistosomiasis, and trachoma.

The methods used to estimate prevalence for each NTD reflect differences in data availability, transmission dynamics, and disease natural history. Across most NTDs, input data are sex- and age-split prior to modelling. Two modelling tools are used most commonly: DisMod Bayesian Meta-Regression (DisMod-MR), a disease modelling framework that estimates internally consistent epidemiological parameters (incidence, prevalence, remission, and excess mortality); and spatiotemporal Gaussian process regression (ST-GPR), a statistical approach that borrows information across geography and time to produce a complete time series of estimates.

Forecasts to 2045 used an ensemble model driven by historical rates of change with varying weights across child models for weighting recent years more heavily, informed by out-of-sample predictive validity. Better and worse scenarios were constructed by applying the 85th and 15th percentile of historically observed rates of change across location-years, respectively.

To estimate the impact of reduced development assistance for health, we used a nonparametric stochastic frontier approach (as detailed in the “Measuring funding cuts to foreign aid and their impact on SDGs” section above) to model how decreased spending—varying by country and year—would increase NTD prevalence and adjusted our forecasts per the reference scenario for each country through 2045 accordingly.

Family planning

IHME estimates the proportion of women of reproductive age (15 to 49 years) who have their need for family planning satisfied with modern contraceptive methods. Modern contraceptive methods include the current use of male or female sterilization, male or female condoms, diaphragms, cervical caps, sponges, spermicidal agents, oral hormonal pills, patches, rings, implants, injections, intrauterine devices (IUDs), and emergency contraceptives.

Estimates are derived from two types of sources: individual-level survey microdata and tabulated survey reports. Major survey series include Demographic and Health Surveys (DHS), Multiple Indicator Cluster Surveys (MICS), Performance Monitoring for Action (PMA) surveys, Generations and Gender Programme (GGP) surveys, and country-specific surveys. From microdata, key variables extracted include contraceptive usage, marital status and sexual activity, fecundity, desire for children, and pregnancy and postpartum amenorrheic status. For tabulated survey reports, estimates of any contraceptive use, modern contraceptive use, unmet need for family planning, and marital status breakdowns are manually extracted. All sources are collapsed to age-specific estimates and combined prior to modeling.

Need for family planning is determined separately for partnered and unpartnered women aged 15 to 49 using the 2012 DHS revised definition of unmet need, applied through a standardized algorithm. Women are classified as having a need through three main pathways: 1) they are currently using any contraceptive method (modern or traditional); 2) they are currently pregnant or postpartum amenorrheic from a birth in the last two years and express desire to have prevented or delayed that pregnancy; or 3) they are fecund, do not want a child in the next two years, and are either married/in-union or have been sexually active in the last 30 days. Unpartnered women must additionally meet a sexual activity criterion that married women are assumed to satisfy automatically. When surveys are missing key components of the algorithm — such as desire for children, fecundity information, or postpartum amenorrheic status — counterfactual re-extractions are performed under alternative assumptions (e.g. assuming all women have a need), and an adjustment factor is estimated and applied to adjust those estimates relative to gold standard surveys that contain full information.

Rather than modeling met need and contraceptive prevalence directly, IHME uses a nested proportions approach that models three underlying components separately: (1) any contraceptive prevalence; (2) the proportion of any contraceptive use that is modern; and (3) the proportion of non-users with unmet need for family planning. Each component is modeled separately for partnered and unpartnered women using spatiotemporal Gaussian process regression (ST-GPR). The Socio-Demographic Index (SDI) is a key covariate in all models. Partnered model results are used as custom covariates in the unpartnered models to account for data sparsity among unmarried women. An additional ST-GPR model of the proportion of women currently partnered is used to aggregate marital-status-specific results to all-women estimates. Modeling proceeds in two stages: preliminary runs use age- and marital-status-specific data only, with results used to split age-aggregated and all-women data; final runs incorporate all available data. Age-aggregated data are split into five-year age bins and all-women data are split into partnered and unpartnered estimates using draws from the preliminary models.

Final estimates for the indicator are calculated by combining draws across partnered and unpartnered estimates using marital status results, then aggregating to all ages. Forecasts to 2045 used an ensemble model driven by historical rates of change with varying weights across child models for weighting recent years more heavily, informed by out-of-sample predictive validity. Better and worse scenarios were constructed by applying the 85th and 15th percentile of historically observed rates of change across location-years, respectively.

To estimate the impact of reduced development assistance for health, we used a nonparametric stochastic frontier approach (as detailed in the “Measuring funding cuts to foreign aid and their impact on SDGs” section above) to model how decreased spending—varying by country and year—would decrease met need for modern contraception and adjusted our forecasts per the reference scenario for each country through 2045 accordingly.

Universal health coverage

The universal health coverage (UHC) effective coverage index is a metric composed of 23 effective coverage indicators spanning population-age groups across the life course: maternal and newborn, children under age 5, youths ages 5 to 19, adults ages 20 to 64, and adults ages 65 and older. These indicators fall within three health service domains: promotion, prevention, and treatment.

The health system promotion indicator is met need for family planning with modern contraception.

Health system prevention indicators include the proportion of children receiving the third dose of the diphtheria-tetanus-pertussis vaccine and the proportion receiving the first dose of measles-containing vaccine. Antenatal care for mothers and antenatal care for newborns are considered indicators of both prevention and treatment of diseases affecting maternal and child health.

Indicators of treatment for communicable diseases include the mortality-to-incidence (MI) ratios for lower respiratory infections, diarrhea, and tuberculosis, as well as coverage of antiretroviral therapy (ART) among people with HIV/AIDS. Indicators of treatment for noncommunicable diseases include MI ratios for acute lymphoid leukemia, appendicitis, paralytic ileus and intestinal obstruction, cervical cancer, breast cancer, uterine cancer, and colorectal cancer, along with mortality-to-prevalence (MP) ratios for stroke, chronic kidney disease, epilepsy, asthma, chronic obstructive pulmonary disease, and diabetes, and the risk-standardized death rate due to ischemic heart disease.

Effective coverage indicators are weighted in the index according to the potential health gain each country could achieve by improving coverage of that indicator.

To forecast the UHC index from 2025 to 2045, we fit a meta-stochastic frontier model using total health spending per capita projections as the independent variable. Country- and year-specific inefficiencies were then extracted from the model and forecasted to 2045 using a linear regression with exponential weights across time for each country. These forecasted inefficiencies, together with forecasted total health spending per capita, were substituted into the fitted frontier to produce forecasted UHC for all countries for 2025–2045. For countries with recent or ongoing conflicts, we also adjusted UHC estimates using ACLED conflict data. From this dataset, we identified seven countries with high severity of conflict and over 5 percent of the population impacted by conflict (Iran, Palestine, Lebanon, Syria, Ukraine, Haiti, Myanmar). For these countries and years impacted by conflict, we reduced UHC estimates by applying the country’s maximum observed inefficiency and scaling the magnitude of the conflict shock by the proportion of the population impacted by conflict. Finally, we linearly attenuated the magnitude of the decline in UHC due to conflict back to baseline levels over 10 years.

References:

Armed Conflict Location & Event Data Project “(ACLED). ACLED: Real-time data and analysis on political violence and protest.” acleddata.com.

Smoking

IHME measures the age-standardized prevalence of any current use of smoked tobacco among those age 15 and older. IHME collates information from available representative surveys that include questions about self-reported current use of tobacco and information on the type of tobacco product smoked (including cigarettes, cigars, pipes, hookahs, and local products). IHME converts all data to its standard definition of any current smoking within the last 30 days so that meaningful comparisons can be made across locations and over time.

Our models are informed by self-reported use of current smoking (occasional or daily use) from validated nationally representative surveys, such as DHS, MICS, GATS, and others. Additional surveys are included as well, based on quality and representativeness. Individual-level data is collapsed into GBD-standard five-year age-sex bins (male or female, ages 10 to 14 through 95+) for each modelled location and year. Tabulated data is split into GBD standard bins via age and sex patterns modeled on location and region-specific individual-level data. Recall periods are cross walked to match our gold standard definition. The full dataset is used to inform a spatiotemporal gaussian process regression model (ST-GPR) of current smoking prevalence. The ST-GPR yields temporally smoothed estimates that incorporate regional influences in data-sparse locations.

To account for the inherent link in the populations of current and former smokers—current smokers who quit become former smokers—we forecast current and former smoking prevalence jointly. We define ever smoking prevalence as the proportion of people who are either current or former smokers and compute the ratio of current to ever smoking prevalence. We then use a generalized ensemble model to forecast 1) ever smoking prevalence and 2) the ratio of current to ever smoking prevalence annually from 2024 through 2045 and recover current and former smoking prevalence forecasts from these two quantities. This model incorporates historical rates of change in conjunction with the relationship between the sociodemographic index and smoking prevalence. Better and worse scenarios are constructed by applying the 85th and 15th percentile of historically observed rates of change across location-years, respectively.

Vaccines

IHME's measurement of immunization coverage reports on the coverage of the following vaccines separately: three-dose diphtheria, tetanus and pertussis containing vaccine (DTP3), measles second dose (MCV2), and three-dose pneumococcal conjugate vaccine (PCV3).

IHME estimates annual vaccine coverage from 1990 to the present using two complementary streams of data: country-reported data (both administrative and official coverage data) and survey data. Country-reported administrative and official coverage are submitted each year through the World Health Organization (WHO)–United Nations Children's Fund (UNICEF) Joint Reporting Form (JRF), which provides near-complete annual time series. Survey data are obtained from nationally-representative household surveys, principally the Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS), supplemented by other multi-country and country-specific surveys. Because country-reported coverage is subject to systematic bias, IHME compares paired survey and country-reported observations from the same country-years, matched by birth cohort, then estimates patterns of bias by country and over time using meta-regression, with the Healthcare Access and Quality (HAQ) Index as a covariate (assuming that reporting bias varies with the general quality of health services). These models are then used to adjust country-reported data for bias prior to inclusion in vaccine coverage models.

Survey and bias-adjusted country-reported data are then used as inputs into spatio-temporal Gaussian process regression (ST-GPR) models, which are used to produce coverage estimates. ST-GPR consists of a three-stage framework that fits a covariate-based regression, borrows strength across space and time to improve estimates where data are sparse, and follows data closely where available and reliable. ST-GPR model covariates include the HAQ Index, mortality due to war and conflict, and vaccine disruptions arising from stockouts, the COVID-19 pandemic, and other events. As in last year's report, pandemic-related disruptions were estimated for the years 2020-2023. To maintain internal consistency across doses and antigens, DTP3 is estimated by modelling the ratio of DTP3 to the first dose of that vaccine (DTP1), then multiplying this ratio by DTP1 coverage estimates, while MCV2 and PCV3 are modelled as ratios to MCV1 and to DTP3, respectively, and constrained to be less than one. Coverage estimates for MCV2 and PCV3 additionally account for scale-up in the years following country-specific vaccine introduction using hierarchical spline models. This approach allows global patterns of scale up to inform country-specific scale-up models, strengthening early post-introduction estimates in locations where data are sparse or absent.

Forecasts to 2045 were modeled using a linear mixed effects model to forecast vaccine coverage, using SDI the primary covariate. For vaccines that have not been universally introduced (MCV2 or PCV3), coverage is modeled as the ratio of MCV2 coverage to MCV1 coverage and the ratio of PCV3 to DTP3 coverage. For countries that have not yet introduced either vaccine, a Weibull distribution parameterized by lag-distributed income, GAVI eligibility status and education attainment is used to simulate introduction years, with coverage scaling up to that of MCV1 or DTP3, respectively. Better and worse scenarios were constructed by applying the 85th and 15th percentile of historically observed rates of change across location-years, respectively.

To estimate the impact of reduced development assistance for health, we used a nonparametric stochastic frontier approach (as detailed in the "Measuring funding cuts to foreign aid and their impact on SDGs" section above) to model how decreased spending—varying by country and year—would decrease vaccine coverage and adjusted our forecasts per the reference scenario for each country through 2045 accordingly.

Sanitation

IHME estimates the proportion of the population with access to safely managed sanitation. As defined by the Joint Monitoring Programme (JMP), a safely managed facility must meet three criteria: (1) is not shared with multiple households, (2) is an improved sanitation facility, and (3) its wastewater is disposed of safely. Safe wastewater disposal can consist of being treated and disposed of in situ, stored temporarily and treated off-site, or transported through a sewer and treated. Safely managed treated wastewater must have received at least secondary treatment. IHME estimated households with piped sanitation (with a sewer connection or septic tank); households with improved sanitation but without a sewer connection (pit latrine, ventilated improved latrine, pit latrine with slab, composting toilet); households without improved sanitation (flush toilet that is not piped to sewer or septic tank, pit latrine without a slab or open pit, bucket, hanging toilet or hanging latrine, no facilities); and wastewater that receives at least secondary treatment for sewer-connected households, as defined by the JMP for Water Supply and Sanitation.

We developed models to estimate three components of safely managed sanitation: 1) the proportion of collected wastewater that receives at least secondary treatment, 2) the proportion of sewer-connected facilities that are safely managed, and 3) the proportion of improved, non-sewer facilities that are safely managed.

Data for estimating the proportion of collected wastewater that receives at least secondary treatment were extracted from Eurostat, Aquastat, the Organisation for Economic Co-operation and Development (OECD), and national surveys. Data for estimating the proportion of sewer-connected facilities that are safely managed were extracted from Eurostat, Aquastat, Demographic and Health Surveys (DHS), UNICEF Multiple Indicator Cluster Surveys (MICS), OECD, and national surveys (Republic of Korea, Singapore, Andorra, Austria, and Ireland). Data for estimating the proportion of improved, non-sewer facilities that are safely managed were extracted from MICS, DHS, Eurostat, and national surveys (Canada, Norway, and the United States).

We estimated the proportion of the total population with safely managed sanitation as the sum of the proportion of the population with safely managed sewer-connected facilities and the proportion of the population with safely managed improved non-sewer facilities.

Forecasts to 2045 were generated using an ensemble model that incorporated both historical rates of change and SDI projections. Component model weights were determined through out-of-sample predictive validity testing, with greater weight assigned to models that more heavily emphasize recent trends. Better and worse scenarios were constructed using the 85th and 15th percentile of historically observed rates of change across location-years, respectively.

To estimate the impact of reduced water, sanitation, and hygiene (WASH) overseas development assistance and government spending, we used a nonparametric stochastic frontier approach (as detailed in the "Measuring funding cuts to foreign aid and their impact on SDGs" section above) to model how decreased WASH spending—varying by country and year—would decrease safely managed sanitation coverage, and adjusted our forecasts per the reference scenario for each country through 2045 accordingly.

References:

World Health Organization and United Nations Children's Fund. SDG Indicator Metadata: Indicator 6.2.1(a), *Proportion of Population Using Safely Managed Sanitation Services*. Updated December 20, 2021. WHO/UNICEF Joint Monitoring Programme PDF

IHME INDICATOR SOURCES

Data source information for each indicator are below, a detailed reporting of data sourcing for GBD 2023 estimates can be found at https://sources.healthdata.org/collection/sources-2023

INDICATOR AND COMPONENT	TOTAL SOURCES
Child mortality	25,260
Child stunting	1,102
Family planning (met need)	1,148
Malaria	13,099
Maternal mortality	8,107
Neonatal mortality	25,260
HIV	7,849
NTD chagas	1,199
NTD visceral leishmaniasis	5,815

INDICATOR AND COMPONENT	TOTAL SOURCES
NTD cutaneous and mucocutaneous leishmaniasis	1,503
NTD African trypanosomiasis	3,075
NTD schistosomiasis	3,855
NTD cysticercosis	3,901
NTD cystic echinococcosis	3,731
NTD lymphatic filariasis	496
NTD onchocerciasis	351
NTD trachoma	109
NTD dengue	3,950

INDICATOR AND COMPONENT	TOTAL SOURCES
NTD rabies	4,058
NTD ascariasis	4,599
NTD trichuriasis	868
NTD hookworm disease	873
NTD food-borne trematodiases	57
NTD leprosy	1,595
NTD guinea worm disease	458
Sanitation safely managed	1,356
Smoking prevalence	3,630
Tuberculosis	8,422
UHC maternal disorders	8,107
UHC met need	1,148

INDICATOR AND COMPONENT	TOTAL SOURCES
UHC live births	16,589
UHC neonatal mortality	25,260
UHC diphtheria	4,479
UHC pertussis	9,667
UHC tetanus	4,679
UHC dtp vaccination	9,005
UHC measles	11,333
UHC measles vaccination	8,893
UHC LRI	4,860
UHC diarrhea	6,087
UHC HIV treatment	7,849
UHC TB	4,842

INDICATOR AND COMPONENT	TOTAL SOURCES
UHC lymphoid leukemia	4,492
UHC asthma	3,349
UHC diabetes	4,627
UHC IHD treatment	4,603
UHC stroke	4,631
UHC Chronic kidney disease	4,381
UHC Chronic obstructive pulmonary disease	3,366
UHC cervical cancer	4,461
UHC breast cancer	4,583
UHC uterine cancer	4,460
UHC colon and rectum cancer	4,550

INDICATOR AND COMPONENT	TOTAL SOURCES
UHC epilepsy	4,370
UHC appendicitis	4,468
UHC paralytic ileus and intestinal obstruction treatment	4,342
Vaccine coverage dtp3	10,035
Vaccine coverage mcv2	3,602
Vaccine coverage pcv3	2,440

INDICATORS ESTIMATED FROM OTHER SOURCES

Poverty

Lakner, C., Foster, E.M., Jolliffe, D., Ibarra, G.L., and Baah, S. *Reproducibility Package for Global Poverty Revisited Using 2021 PPPs and New Data on Consumption*. Data set. RR_WLD_2025_346. World Bank, 2025. doi.org/10.60572/qmda-qt67.

For methodology, see: World Bank, *Global Poverty Revisited Using 2021 PPPs and New Data on Consumption*, Policy Research Working Paper 11137, Washington, DC: World Bank, 2025. documents1.worldbank.org/curated/en/099503206032533226/pdf/IDU-e2e09dcf-0af2-481a-a60a-64adf28171d0.pdf.

This report uses the international poverty line and purchasing power parity (PPP) data incorporated in the World Bank's June 2025 update, which raised the international poverty line from $US2.15 a day (2017 PPP) to $US3.00 a day (2021 PPP). This update is reflected in the current edition to ensure consistency and comparability with the World Bank's current global poverty methodology.

Agriculture

Food and Agriculture Organization of the United Nations. *Income of Small-Scale Food Producers, PPP (Constant 2011 International USD)* Data set, SDG Indicator 2.3.2, Dataflow DF_SDG_2_3_2, series SI_AGR_SSFP FAO Data Explorer, 2025. de-public-statsuite.fao.org.

Small food producers' income growth is included for selected countries with at least two data points in the data set. For each country, income growth is calculated between the earliest and most recent years available, except where specific data points were excluded following expert review of data quality. The specific years used for each country are listed below:

LOCATION	YEAR RANGE
Benin	2019–2021
Burkina Faso	2014–2021
Cambodia	2009–2021
Côte d'Ivoire	2008–2019
Ethiopia	2014–2019
Ghana	2013–2017
Guinea-Bissau	2019–2021
India	2005–2012
Malawi	2011–2020

LOCATION	YEAR RANGE
Mali	2014–2021
Niger	2011–2019
Nigeria	2013–2019
Pakistan	2011–2019
Senegal	2011–2022
Sierra Leone	2011–2018
Tanzania	2009–2021
Togo	2019–2021
Uganda	2010–2020

Education

World Bank, UNESCO Institute for Statistics, UNICEF, USAID, Bill & Melinda Gates Foundation, & Foreign, Commonwealth & Development Office, *The State of Global Learning Poverty: 2022 Update*. Conference Edition, 2022, www.unicef.org/media/122921/file/StateofLearningPoverty2022.pdf.

Source for Learning Poverty 2022 simulations:

Azevedo, J. P., Demombynes, G., and Wong, Y. N., "Why Has the Pandemic Not Sparked More Concern for Learning Losses in Latin America? The Perils of an Invisible Crisis," *Education for Global Development*, 2023. blogs.worldbank.org/en/education/why-hasnt-pandemic-sparked-more-concern-learning-losses-latin-america-perils-invisible.

Gender equality

The Equal Measures 2030 (EM2030) SDG Gender Index is the most comprehensive global tool to measure progress toward gender equality aligned to the SDGs. The index tracks 56 key gender indicators that provide the "big picture" across and within 14 of the 17 SDGs.

It is the only index that adds a gender lens to each of the goals, including the many SDGs that lack such a lens in the official framework. Going beyond SDG 5 (the single goal dedicated to gender equality) is important in capturing the broader trends that influence progress on gender equality and highlighting how issues such as hunger, poverty, and climate change affect girls and women.

The 2024 index covers 139 countries, which represent 96 percent of the world's women and girls. The index tracks scores for three reference years: 2015, 2019, and 2022 and forecasts a scenario for 2030 based on current trends.

This is the third edition of the SDG Gender Index—it was previously released in 2019 and 2022. It is one of the few global gender indices to be formally audited by the European Commission Joint Research Centre's Competence Centre on Composite Indicators and Scoreboards (JRC-COIN). The fourth edition of the SDG Gender Index will be released by Equal Measures 2030 later this year.

The index was developed by a coalition of national, regional, and global leaders from feminist networks, civil society, and international development.

Resources:

To download 2024 index data and the latest index report and for more information about index methodology, see: www.equalmeasures2030.org/2024-sdg-gender-index

To access interactive index data visualizations, see: www.equalmeasures2030.org/2024-sdg-gender-index/explore-the-data/

To view the technical audit conducted by the COIN center of the EU's Joint Research Centre, see www.equalmeasures2030.org/2024-sdg-gender-index/about-the-index/

Equal Measures 2030. A Gender Equal Future in Crisis? Findings from the 2024 SDG Gender Index. 2024 www.equalmeasures2030.org/2024-sdg-gender-index.

Inclusive financial systems

The "income" comparison refers to what the World Bank calculates as account ownership of the richest 60 percent of households versus the poorest 40 percent of households.

Klapper, L., Singer, D., Starita, L., and Norris, A., The Global Findex Database 2025: *Connectivity and Financial Inclusion in the Digital Economy*. Washington, DC: World Bank, 2025. doi.org/10.1596/978-1-4648-2204-9.

World Bank. "Account Ownership at a Financial Institution or with a Mobile-Money-Service Provider (% of Population Ages 15+)." *Global Findex Database*. Data set. 2025. genderdata.worldbank.org/en/indicator/fx-own-totl-zs

For methodology, see:

Klapper, L., Singer, D., Starita, L., and Norris, A. "Survey Methodology." Appendix A in *The Global Findex Database 2025: Connectivity and Financial Inclusion in the Digital Economy*, 267–294. Washington, DC: World Bank, 2025. www.worldbank.org/en/publication/globalfindex/methodology.