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Research Paper

Predictive tools in maternal health: Making futures for patients and populations

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Researchers develop tools from population data to predict health outcomes for individuals and for groups. Clinicians use some of these predictive tools to guide medical interventions; policymakers use other predictive tools to allocate funds and inform policy decisions. Building on critical metrics scholarship, ethnographic research, and medical experience in Malawi and the United States, I first review how clinicians use three tools—height measures, partographs, and Vaginal Birth After Cesarean calculators—as decision aids in obstetrical care. Each tool was designed to predict and avert devastating obstetric outcomes. Each has been used globally for millions of women, shaping actual futures by forecasting probable ones. Predictive tools provide important guidance. They also share limitations: they can incorporate feedback loops, naturalize biases, and misdirect attention from alternative possibilities. Those problems may scale up into the increasingly complex global-health projections used by policymakers to guide public-health decisions. Without systematic vigilance, health-related predictive tools may have unhealthy unintended consequences. Extrapolation from what we know about simpler clinical tools provides researchers with vulnerabilities to investigate, and ideas about how we might reimagine population-level predictive tools to build a healthier future.

Introduction

Clinicians use many predictive tools: decision-making aids, developed by researchers from population studies, that incorporate an individual patient's data to predict likely futures. These tools guide medical decisions intended to avert bad futures and invite good outcomes.

An example: a patient with postpartum sepsis needs a powerful antibiotic. How much should she get? Her doctor must predict how quickly the patient's kidneys will filter the drug from her blood. Kidney-function measurement is too invasive, expensive, and slow. Clinicians use a noninvasive, inexpensive, and quick prediction tool instead:

C_{cr} in milliliters/minute = ([140 - age in years] × [weight in kilograms]) / (72 × [serum creatinine in milligrams/deciliter]); multiply the result by 0.85 for women.

The resulting C_{cr} (creatinine clearance) number helps us to calculate dosages high enough to vanquish infection but low enough to prevent toxicity.

Researchers developed this predictive tool by correlating measured kidney function with age, weight, and serum creatinine—a simple blood test—among 249 Canadian men. Because women's renal clearance was estimated to be 80-90% that of men's, the tool's developers chose an 85% multiplier for women (Cockcroft & Gault 1976).

Graphically, a researcher designing a clinical predictive tool might think like this:

POPULATION DATA → CORRELATION OF DATA PARAMETERS WITH OUTCOMES → PREDICTIVE TOOL

while a clinician using it might think like this:

INDIVIDUAL'S PARAMETERS
↓
POPULATION DATA → PREDICTIVE TOOL
↓
INDIVIDUAL'S LIKELY FUTURE → APPROPRIATE CLINICAL ACTION

Other predictive tools work at the population rather than the patient level. Health policymakers use the Global Burden of Disease (GBD) projections, for instance, to plan staffing and infrastructure to meet future population needs (Misganaw et al. 2023). Udevi-Aruevoru (2026) describes another example: the Lives Saved Tool (LiST) allows policy makers in low- and middle-income countries to predict likely maternal, infant, and child mortality effects of future interventions. Population data used for predictive tools can involve surveys, insurance or health records, or even 'big data' sources such as grocery transactions and internet search records (Ramezani et al. 2023). A policymaker's perspective on such tools might look like this:

NATIONAL / REGIONAL PARAMETERS
↓
POPULATION DATA → PREDICTIVE TOOL
↓
NATION'S / REGION'S LIKELY FUTURE → APPROPRIATE POLICY INTERVENTION

Predictive tools work across time, using past data to guide present action to invite desirable futures. They shape actual futures by forecasting possible ones. In this paper, I argue that public health researchers may foresee limitations of predictive tools for global health decision-making by considering the complex effects of predictive tools used to aid decision-making for individual patients.

For this conceptual essay, the object of study is the predictive tool. I take as key examples three commonly used in obstetric practice: height measures, partographs, and vaginal-birth-after-cesarean (VBAC) calculators. All three are used to predict risks, guiding clinicians and patients to decisions that will optimize outcomes for mother and newborn. Each has been studied by other scholars. In work as an obstetrician, in the USA and in Malawi, I used them, saw them used, and discussed them with colleagues. In work as an anthropologist in Malawi, I observed height measures and partographs in use and discussed predictive practices (in English and Chichewa) with experts in pregnancy and birth care. While I draw on those observations and discussions, the tools were not the research focus: maternal death was (Wendland 2022).[1] Nothing described here is intended as a critique of obstetric practice in Malawi or the United States. The essay itself is a predictive tool, drawing on existing data to identify actions that could lead to better tool designs and therefore better global health futures.

Predictive tools embed theories of causation: theories about the fundamental causes of obstructed labor, or maternal death, or uterine rupture. The assumptions built into each tool are buried in charts and equations, however. Dressed in quantification, these heuristics appear atheoretical. The predictions they produce are disguised as facts. I build in this article from feminist scholarship on reproduction and critical metrics studies to show what that disguise obscures, and how researchers might do better.

Three Clinical Predictive Tools

Height Measure: Is This Mother So Small We Should Expect Trouble?

Researchers find greater risks of difficult labor among smaller women no matter where they divide short from not: an early study found that Scotswomen below five feet tall were more likely to need labor assistance than those above five feet five inches (Bernard 1952); a larger 20-country analysis found greater need for obstetrical interventions to correlate with below-national-average height (Kelly et al. 1996). At its worst, difficult labor can become obstructed, an outcome much dreaded by Malawian clinicians. Epidemiologists estimate that obstructed labor, in which a fetus becomes jammed in a woman's pelvis, causes one in ten maternal deaths and nearly all obstetric fistulae worldwide (Maharaj 2010).

To prevent this unwanted future, Malawi's antenatal-care protocols dictated that anyone shorter than 150 cm should be referred for delivery to a hospital with an operating theater, where cesarean surgery—the typical treatment for obstructed labor—could be done if necessary. A 2015 Ministry of Health report indicated that 24% of births in Malawi happened in places capable of cesarean section (Ministry of Health 2015). Even where staff, facilities, and supplies are available, the wait for cesarean can be long. Early identification of anyone likely to need surgery could save lives.

Malawi's simplest predictive tool, then, is a height measure. At a busy urban clinic, nurse-midwives asked patients to stand on a scale with a sliding arm that came down to the top of their heads. In a rural health center without such a scale, a medical assistant assessed his client's height against a horizontal line painted on the wall 150 cm from the floor. Hospital trainings for traditional birth attendants had once included instructions to use a stick with a crossbar nailed at 150 cm (Bullough 1979). (Trainings had been discontinued for years, and I never witnessed such a stick in use.) A few midwives and traditional birth attendants I interviewed used their own bodies to measure: is she shorter than me? How much? A community-health workers' manual simply recommended hospital referral for very short ('*aafupi kwambiri*') women (Werner et al. 2006, p. 283).

Partograph: Will This Labor Need Intervention?

The partograph is a one-page chart designed to identify labors destined for trouble. Height measurements are used before labor, partographs during labor. They share a goal: prevent obstructed labor by prompting early intervention. Once labor begins, a woman's cervical dilation, estimated by the

[1] Individuals' names are pseudonyms, as required by the UW-Madison IRB (protocol #SE-2012-0223) and the University of Malawi College of Medicine Research Ethics Committee (P.05/06/492), which oversaw the research.

clinician's fingers during a vaginal exam, is plotted on a chart marked with hourly intervals (see Fig. 1). Two diagonal lines are key to the chart's use to prevent obstructed labor. The *alert* line is based on a smoothed version of the tenth percentile for labor progress among an unspecified number of African women in their first labors at the University of Rhodesia's teaching hospital in the 1960s (Philpott & Castle 1972). Four hours to its right a parallel line demands *action*. When a line drawn between measures of cervical dilation crosses the alert line, the clinician should pay closer attention, considering ways to support more effective labor. When the action line is crossed, it's time to do something: rupture her amniotic membranes, perhaps, or recommend a cesarean, or start an oxytocin drip.

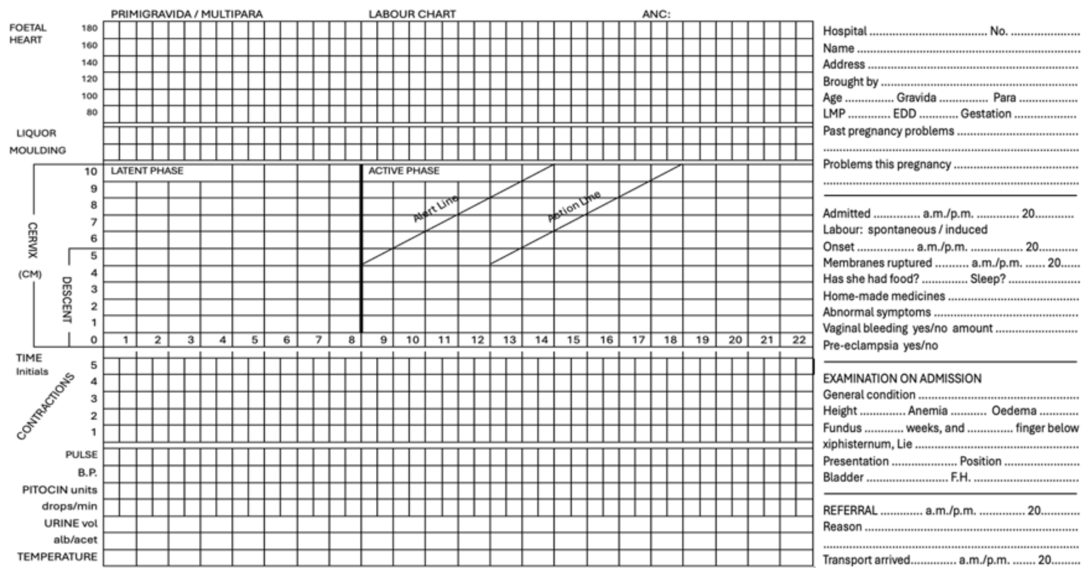

Figure 1: The partograph as used in Malawi. *Source:* Redrawn from Wendland 2022, p. 121.
Note: Because the partograph can serve as a complete labor record, it also provides space for other observations.

VBAC Calculator: Will She Deliver Vaginally?

Another predictive tool, the VBAC calculator, seeks to avert obstetrical disaster for people who have previously had cesarean surgery. A healed uterus does not have the same integrity and strength after a cut. After a single prior cesarean, maternal and neonatal outcomes are generally good with either vaginal birth or planned repeat cesarean; trying for vaginal birth and failing, however, is more dangerous for both mother and infant (Guise et al. 2010). People attempting VBAC are more prone to serious and sometimes lethal complications than those who have never had a cesarean (Guise et al. 2010). Risks multiply with every additional cesarean section, and are probably much greater in resource-restricted contexts (Turner 2023). Clinicians would find accurate prediction useful: whose trial of labor—as obstetricians call it—is likely to result in a vaginal birth after cesarean? Whose is not?

Researchers developed a predictive tool by analyzing outcomes among almost 12,000 women whose trials of labor followed a single uncomplicated prior cesarean, across 19 American medical centers, using multiple logistic regression to calculate how strongly various parameters correlated with VBAC (Grobman et al. 2007). Technically, the predictive graphic tool they built was a nomogram (Fig. 2). Practically, it became known as 'the VBAC calculator.' (I'll call it the Grobman calculator, as clinicians do occasionally use others.)

Widely used in the US, especially after a user-friendly online version was released, the Grobman calculator was not part of standard protocols in Malawi. It has been used elsewhere on the African continent, and in Asia, Europe, and the Pacific (Deng et al. 2022).

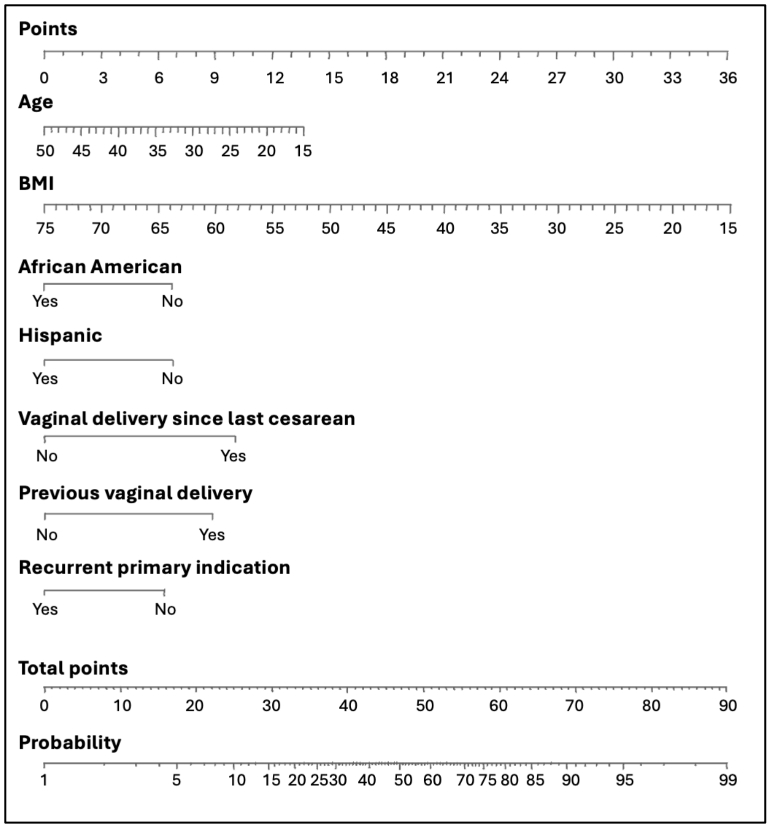

Figure 2: Representation of the original VBAC calculator. Redrawn from Grobman et al. 2007, p. 810.
Note: To use, with a straightedge, align patient data for each parameter with the 'points' scale. Sum points. Line up 'total points' with 'probability.'

How Clinicians Use Tools

Clinicians use predictive tools to guide difficult decisions. Their standardization reassures us that we are following peer-approved best practices, not idiosyncratic preferences. They also help us to justify recommendations, and (often) to relocate responsibility. A height measure below a cutoff allows a medical assistant to insist that his patient be sent to the district hospital for delivery, rather than staying at the local health center. In a Malawian university hospital, a junior midwife who finds that the partograph predicts a dysfunctional labor shifts oversight to the on-call intern. In a US university hospital, a VBAC-calculator score below a designated cutoff dictates a patient's transfer from the midwife team to the physician team.

What's the Problem?

Do height measurements, partographs, and VBAC calculators improve patient outcomes? Unclear. Often, health workers do not use tools as originally intended (Olivier de Sardan et al. 2017, Khonje 2012, Rubashkin et al. 2024). Even when used as designed, however, these tools don't predict the future very well. (For the partograph, see Lavender et al. 2012. For the VBAC calculator, see Thornton 2023. No solid evidence addresses height measurements, but as Campbell and Graham (2006) note, the strategy of high-risk screening and hospital referral has long proven ineffective.) Worse, they may cause trouble.

Tools Can Generate Feedback Loops

Predictive tools do not reveal a future: they shape it. Actions prompted by the tool can worsen outcomes for individuals even while appearing to confirm the theory embedded in the tool, creating feedback loops. Nurse-midwives in Malawi pointed out that transferring a frightened youngster to an unfamiliar hospital where no companion is allowed at her side—whether dictated by a height measure or a partograph—often causes dysfunctional labor. The increased interventions that follow appear to confirm the need for the transfer, even if they were created by it.

The VBAC calculator is intended to shepherd both clinicians and patients to pathways that will produce healthy outcomes. These scores have effects on clinicians and patients (Rubashkin et al. 2024). If people with low odds of success opt not to try for VBAC, many failed trials of labor and unplanned cesareans will be averted—but many VBACs that would have been successful are also averted (Thornton 2023). If a woman whose score is low chooses a trial of labor, but labor slows, her obstetrician may be quicker to recommend surgery and she may be quicker to capitulate, thus implicitly confirming the rightness of the calculator.

Tools Can Naturalize Bias

Some predictive tools disguise bias as biology. Naturalized bias can combine with feedback loops to exacerbate health inequities.

The original VBAC calculator incorporated 'race,' substantially reducing the predicted probability of successful vaginal delivery for patients designated as Black or Hispanic. In a clinical world of tremendous genotypic and phenotypic diversity, the tool reified 'Black' and 'Hispanic' as clearcut yes-or-no biological categories that put people at risk. This assumption fits easily within a broader framework in US medicine, in which 'race' serves as a commonsense proxy for presumed genetic difference (Hunt et al. 2014). Clinicians using the calculator to counsel Black and Hispanic patients about VBAC were more likely to encourage repeat cesarean because of the lower scores that the calculator produced (Rubashkin et al. 2024). Excess surgical morbidity among those patients could then tacitly confirm that they were 'high risk' from the start.

Long after studies showed the calculator to underpredict successful VBAC among minority patients (Thornton 2023), the tool's designers revised it to remove race and ethnicity in 2021, during a period of heightened concern over institutionalized racism spurred on by George Floyd's murder. Examination of other decision-making aids that used race as a variable revealed several problems: some generated risks of undertreatment for minoritized people when treatment was necessary; others posed risks of overtreatment in cases when watchful waiting might have better preserved patients' health (Vyas et al. 2020).

Tools Can Misdirect Attention

As theories of bad outcomes, and as prompts for health-promoting action, predictive tools can misdirect attention away from key concerns (Peeters Grietens et al. 2022). Some nurse-midwives and some traditional birth attendants in Malawi suggested that a focus on height was misplaced, for instance. It was scared girls ill-prepared to calm down and push who were the problem, not short women.

The VBAC calculator also misdirects. It predicts *whose* trial of labor will end in a successful VBAC, and *whose* will not. It does not predict *where, how,* or *with whom* a trial of labor is most likely to end well. The exclusive focus on patients' racialized bodies misdirects attention. The availability of midwifery care or doula support; provider enthusiasm; patient volumes; call schedules; institutional cesarean-section rates: all are critical predictors of VBAC success (Thornton 2023). None were included in the calculator.

Scaling Up Futures: Predictive Tools for Policy

Tools used clinically scale down from population data to aid decision-making for individuals. Predictive tools used for policy scale up to influence national decisions—such as allocating money, medications, equipment, and staff. These predictive tools have real impact. Malawi's maternal mortality projections contributed to policy responses intended to maximize facility birth: a ban on traditional birth attendants; fines for families of women who delivered at home (Banda 2013, Wendland 2022). Malawi was not unique. In the run-up to the Millennium Development Goals, projected maternal mortality figures sometimes incentivized policy actions that undermined care (Oni-Orisan 2016, Strong 2020).

Like clinical predictive tools, population forecasts can reassure policy makers that they are following evidence-based best practices rather than whims. LiST is one such tool. Others come from the WHO and from the Institute of Health Metrics and Evaluation (IHME). The IHME, which produces the GBD visualizations and projections, describes its aim as 'providing an impartial, evidence-based picture of global health trends' to enable policymakers to 'best dedicate resources to maximize health improvement' (Institute for Health Metrics and Evaluation n.d.).

Predictive tools used for policy share some limitations with those used for clinical decision-making, because they are structurally similar. Each uses past data to project futures, selecting a few indicators from many possibilities based on availability and (usually) on a theory of pathogenesis. Indicators that are not widely available, such as institutional cesarean section rates, cannot be incorporated into a VBAC calculator no matter how important they might be. Indicators not imagined to be relevant because they do not fit the theory of individual bodily pathology, such as call schedules, will not even be considered. These limitations will affect clinical and policy predictive tools alike.

POPULATION DATA	→	CORRELATION OF DATA PARAMETERS (selected based on availability and theory of pathogenesis) WITH OUTCOMES	→	PREDICTIVE TOOL

Clinical and policy forecasting tools also share a certain opacity that inhibits critical engagement. Researchers build and publish them. End-users often implement them without further interrogation. As a practicing obstetrician, I used the creatinine-clearance formula to predict renal function many times without learning about its development until now. Partographs are included in every laboring woman's file at the hospital in Malawi where I worked, but in teaching rounds and lectures over the years, I never heard their origins discussed. Global-health predictions are similar; many users do not or cannot explore to see how a proposed intervention's effectiveness was calculated (Roberton et al. 2017).

An additional vulnerability affects policy tools. In clinical predictive tools, most inputs (height, cervical dilation) are measurements. In policy tools, they are estimates. Maternal mortality projections may require fertility or HIV-seropositivity rates, for example. These numbers are all estimates, often rough ones. Tools to assess possible policy interventions require quantifications of anticipated effectiveness. Efficacy estimates move across time and space. Experience from Bangladesh may be used to anticipate effects in Malawi, data from Malawi used to calculate effects in Nepal. Figures from 2012 may be used to project policy impact in 2040.

For instance, blood transfusion should prevent 14.26% of Malawi's maternal deaths, LiST predicts.[2] How was this figure derived? Three dozen maternal-health experts (including five with experience on the African continent) were polled in three rounds until they converged on estimates that transfusion would avert a quarter of maternal deaths from sepsis and half from hemorrhage, globally (Pollard et al. 2013). Meanwhile, statistical modelers estimated that 9.92% of maternal deaths in the African region resulted from sepsis and 23.56% from hemorrhage. The modeled figures' exactness concealed very large uncertainties: the 95% confidence interval for the 23.56% hemorrhage figure ran between 5% and 55% (Say et al. 2014). LiST's formula multiplies the modeled figures by the experts' estimates of how often transfusion might prevent death: (0.25 x 9.92) + (0.5 x 23.56) = 14.26. A precise number comes from imprecise processes.

Health officials predicting whether the expense of expanding blood transfusion services will meaningfully reduce maternal deaths depend on numbers like these to forecast policy effects. These tools are important ways to envision possible futures, and their designers have put much creative effort into making them as useful as possible. However, projections built on foundations of multiple estimates are far less sturdy than the precise numbers they generate make them appear.

Do Problems With Predictive Tools Scale Up?

Policy-level predictive tools may have unanticipated effects similar to those of clinical predictors, at a larger scale. While my evidence is more limited here, there are indications that policy tools too can self-fulfill through feedback loops; naturalize biases; and misdirect attention from alternative paths to achieve desirable futures.

Feedback Loops at Scale

Large-scale predictive tools require baseline health numbers, such as percentages of deaths attributable to specific causes. Because diagnoses do not directly reflect prevalence of pathology (Menéndez et al. 2021), these attributions may produce feedback loops. Clinics in many African regions, for instance, are more likely to have diagnostic kits for malaria and HIV than computed tomography scanners (Sanuade 2021). A pregnant patient presenting with a terrible headache and cognitive changes will be more readily diagnosed with cerebral malaria even if her symptoms result from cerebrovascular disease—and the malaria parasites in her blood are coincidental. Regional projected burdens of disease built on data aggregated from these clinics will overemphasize malaria and underestimate cerebrovascular thrombosis. The resulting projections will drive additional attention and resources: malaria diagnostics and antimalarial medications will be prioritized over the brain imaging and thrombolytics useful for stroke.

Similar loops distort projections of effectiveness. In Senegal, safe abortion provision is not politically palatable, but post-abortion care (PAC) involving manual vacuum aspiration and contraceptive counseling is. Accurate evaluation of how well PAC works to prevent maternal death would require accurate counting of abortion complications and of deaths attributable to them. Clinicians, however, are

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[2] To work through, go to https://www.livessavedtool.org/. Source details are supplied in the online technical notes.

under strong pressure to please donors and politicians by demonstrating that investment in PAC is effective—and therefore selectively misclassify many abortions as miscarriages (Suh 2021). Under-reporting of suspected clandestine abortions furthers the impression that PAC 'works' to protect women. Rajkotia (2018, p. 1) has described this kind of situation, in which no one has an incentive to look too closely at the numbers, as a 'success cartel.' Faulty data keeps clinicians out of trouble, protects at least some women from criminal abortion charges, and ensures that donors reward the health ministry with funding for yet more PAC tools and services (Suh 2021).

Naturalizing Bias

The Grobman calculator naturalized inequities by assuming that the observed lower rates of VBAC among women categorized as Black and Hispanic meant something about their bodies, not something about their care (Thornton 2023). Inequity can be naturalized at population levels too, a phenomenon known as algorithmic bias.[3]

LiST and GBD projections naturalize economic inequities. LiST's developers caution that it is intended only for use in low- and middle-income countries. Why? The tool comes pre-equipped with various low-cost interventions to consider, and with two implicit assumptions: 1) that any low-income place—from Afghanistan to Zambia—might reasonably choose these pre-loaded interventions; and 2) that foreclosure of expensive options is inappropriate for high-income countries. GBD forecasts also build in a narrow list of interventions: seven vaccinations, two antiretroviral regimens, and contraceptives (Misganaw et al. 2023). These narrow choices shape policy. Health ministries in several countries, including India and Malawi, have used LiST to prioritize interventions (Stegmuller et al. 2017); public-health officials in Ethiopia advocated for GBD's tool to identify policy 'best buys'—most health at least cost (Misganaw et al. 2023, p. 1). Each tool builds in quantitative value-for-money predictions. These predictions naturalize business models for health policy, replacing political debate with technical calculations (Merry 2011). By ignoring the costs of patent protection, debt service, brain drain, and other problems created and perpetuated by extractive capitalism, they also naturalize transnational inequities as facts rather than processes subject to intervention (Storeng & Béhague 2017, Udevi-Aruevoru 2006).

Misdirection

Indicators used to model global, regional, and country-level maternal mortality must be both widely available and plausibly related to maternal death. Many demonstrably important factors are missing. As the 2015 Millennium Development Goals neared, for instance, both major forecasters released global projections (see Wendland 2016, Wendland 2022). GDP was the sole economic parameter in both models. No measure of structural adjustment, income inequality, or health-care spending was included. Measures of gender equity were absent, as was abortion access. Both models incorporated HIV prevalence, but neither included treatment: countries where most people could access antiretroviral therapy were analyzed no differently than countries where it was unavailable.

Clinicians in Malawi understood that HIV medications made unaffordable by patent protections, abortions made unsafe by law, and economic policies imposed by global lenders worsened maternal death there. Later calculations by political economists (Coburn et al. 2015, Thomson et al. 2017) confirmed that structural adjustment policies dramatically increased both maternal and child mortality. But the models directed attention away from social and structural issues.

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[3] Panch and colleagues (2019) identify algorithmic bias 'when the application of an algorithm compounds existing inequities in socioeconomic status, race, ethnic background, religion, gender, disability or sexual orientation to amplify them and adversely impact inequities in health systems.' Many uses of health-adjusted life-expectancy measures in algorithms used for policy would qualify under this definition.

Distortions Are Hard to Detect

Most predictive tools used for clinical care are relatively straightforward to understand, test, and modify. Of those described here, the VBAC calculator is the most complex, but anyone who studies it can figure out how it works and where the likely weak points are.

Projections intended to influence policy pose much greater challenges. Two decades ago, details of most tools used to project maternal mortality were published and could be analyzed by interested outsiders. LiST still can be, but many others cannot. By 2014, software programs used in contemporary global health forecasting were drawing from thousands of published and unpublished data sources (Kassebaum et al. 2014), although at that point the key variables used in most equations could still be analyzed. Contemporary projections often use machine learning to evaluate possible models. Model details are not broadly available. When AI is involved, models may not be fully accessible even to their creators. The variables included are rarely transparent, the data itself is sometimes proprietary.

These black-boxed processes make systemic problems difficult to detect. But there is reason to worry. Data can be low quality, or junk.[4] Digital data can mislead (Duclos 2019). Biases present in the digital world—overrepresentation, underrepresentation, misrepresentation of particular groups—distort the data on which advanced computing tools are trained and with which they work (Panch et al. 2019). Machine learning does not eradicate bias by removing human judgment. Like the simpler clinical predictive tools, but less easily detectable, it systematizes and formalizes human judgments that may be profoundly biased.[5]

Designers of predictive tools used to shape reproductive-health policy face particular challenges. As scholars of reproduction have long pointed out, political and religious institutions regulate gender, race, and class in part through management of the 'right' way to conceive, carry, deliver, attend the birth of, or feed a child (a phenomenon Morgan and Roberts (2012) named 'reproductive governance'; see also Ginsburg and Rapp (1995)). Because women's health is politically fraught, some research questions go unasked. Some data are systematically skewed. Misclassification of abortion complications is one clear example (Suh 2021, Morgan & Wendland 2025). Underreporting of maternal deaths is another (Oni-Orisan 2016, Melberg et al. 2019, Strong, 2020).

Even when the data are good, predictive tools may not work out of context. Projections made by the IHME use digital records from data-rich sources (insurance-claim databases, electronic health records, corporate wellness programs, state surveillance systems…) to develop models that are then applied to data-poor contexts (Mahajan 2019). But data-rich places are often also rich in other ways. Elements in models function quite differently from one place to another (Erikson 2018). Public-health professionals can expect that facility birth will have a greater effect where birth in a facility guarantees rapid access to surgery, anesthesia, blood products, and specialty care. Restrictive abortion laws will be less lethal where both self-managed medication abortion and high-quality emergency care are reliably accessible.

[4] Junk scooped up by AI will increase given copy-and-paste practices and prepopulated electronic health-record templates. Timesaving templates (e.g. standardized delivery notes) tend to replace documentation of what actually happened with a description of what is typically expected to happen (Bernat 2013).

[5] Analysts can interrogate machine learning algorithms to better understand biases built into predictions (Kleinberg et al. 2018). I am unaware of such interrogations in the realm of global health—yet.

A Caveat: Prediction ≠ Prescription

The prescriptive power of predictive tools has limits. Sometimes predictions—of VBAC success, of abortion complications, of maternal deaths—prompt action. Sometimes, however, policymakers or clinicians who prefer other interventions ignore them.

Anthropologists working in several contexts have demonstrated that partographs are often filled out after delivery, post-hoc 'predictions' justifying what was already done (Olivier de Sardan et al. 2017, Strong 2020, Melberg et al. 2018). Researchers at one Malawi hospital found that most partographs were completed—but not used to guide decisions about intervention (Bakker et al. 2021). At a rural health center in Malawi, nurse-midwife Delhi Msukwa did not transfer clients under the 150-centimeter cutoff who'd had babies before. The transfer policy wasn't practical, given costs to women and families. Nor was it necessary. 'Look at me, even I am short!' she explained. 'But I deliver easily.'

Experience could cast doubt on predictions made for populations too. In 2007, Rhoda Nantongwe, maternal-child health coordinator for a large district, disputed researchers' projections of a fall in abortion-related deaths in Malawi: 'I don't know how they are doing it.' Septic abortion accounted for half the district's maternal mortality, she estimated, glancing at the maternal-death audits she had compiled. How could abortion deaths drop without legal provision of safe abortion? In 2013, a senior nurse-midwife and I stood side-by-side in a referral hospital, observing a funeral procession coming from the labor ward to the mortuary. Some projections had Malawi on track to reach the Millennium Development Goals' maternal mortality target by 2015, my colleague noted. She didn't believe them. 'If it's that low, why are we still seeing this kind of thing every day?'.

Meanwhile, clinicians and policymakers often act to avert bad outcomes in ways unsupported by population data. American obstetricians use continuous electronic fetal monitoring in labor to predict and prevent neonatal death or cerebral palsy, although evidence shows it prevents neither (Alfirevic et al. 2017). In Malawi, and in many other resource-limited places, health officials and politicians organize funds to build maternity waiting homes where high-risk pregnant people await labor near a hospital. The largest systematic survey found 'insufficient evidence on which to base recommendations' on waiting homes to improve maternal or newborn outcomes (van Lonkhuijzen et al. 2012, p. 2); they are not included in the LiST or GBD tools. Yet policymakers continue to champion this cheap, visible, and intuitively appealing intervention.

We cannot assume that either clinical or policy predictive tools will be accepted uncritically or will drive action in any straightforward way. But they do drive some actions, and they do shape actual people's odds of living and dying.

Where Could We Go From Here? Projecting Alternatives

Predictive tools are powerful and useful. Abandonment of tools in favor of clinical and policy anarchy, inevitably complicated by clinician and politician self-interest, is a poor alternative. A better alternative is better tools.

Current predictive tools, because they use past population data, can only project futures that proceed incrementally from what has already happened. Two implications follow: tools must be scrutinized with the known biases of the status quo in mind; and tool designers must actively seek out alternative imaginations of the future.

Developing or using predictive tools without considering bias risks entrenching inequity (Ghassemi & Nsoesie 2021). Because many health researchers and practitioners are now grappling with structural racism, predictive *clinical* tools will likely face heightened scrutiny for racial bias. The same cannot be said for the black boxes that predict population-level outcomes. How might racism, sexism, neoliberal policy prescriptions, or Western dominance be built into databases, and how could predictive models built on those databases further inequities?

LiST's developers created a what-if 'equity tool' that allows policymakers to project health outcomes for a nation's population as if every citizen had access to the health care that the wealthiest quintile uses. Equity tools need not stop at national borders. What if developers built tools that imagined redress for colonial or neocolonial inequities? What if a policy maker could project maternal health outcomes for Malawians based on health-care interventions available to—say—the British, whose national resources derived in part from colonizing central Africa?

Building better tools will require collaboration and imagination. Local clinicians, health officials, data specialists, and medical social scientists may be important checks for both bias and plausibility. Rhoda Nantongwe would have urged researchers applauding a projected fall in abortion-related deaths to look critically at their sources. The IHME's estimate of maternal deaths for Malawi in the early 2000s, an estimate used to project into the future, was so high it would have translated to a maternal death every two weeks in a typical urban health center that oversaw 25 or 30 average-risk births a week (Wendland 2016). Alongside many other clinicians, I was there: while we saw many deaths, we weren't seeing *that* many. Meaningful local consultation could have spurred a rethinking of this model.

Predictive tools cannot incorporate the unanticipated. The digital trails created by some human interactions, embedded in current predictive tools, lead us only to some possible futures. They project forward a status quo in which business logics and neoliberal policies reign unchallenged. That is a design choice, not an inevitability. It is also a political choice, one that shuts down alternative politics. Other sources of imagination will be critical to generating different tools in which other futures become visible, and the policies to create them become possible goals. Clinicians, community reproductive-justice advocates, ethnographers, and others who attend carefully to people's lives and dreams (thwarted or realized) could be sources for more disruptive and more equitable visions of the future.

Predictive health models could incorporate accountability at levels beyond the national health ministry. A tool that could project the costs in lives and health of food-price volatility, for instance, could help trade negotiators and public health specialists work together to advocate for curbs on grain speculation. Simulated health outcomes of gender equity, debt forgiveness, land reform, trans-Atlantic slave trade reparations, or a universal basic income could alter the kinds of policies imaginable.

Predictive tools, projections, and models in global health are intended to improve people's futures. They must be evaluated against that purpose. When they fail, both theory and data need interrogation. This paper has offered ideas about how to learn from clinical predictive tools to assess questionable assumptions and unintended effects in population-health projections. Software developers, algorithm designers, and people who disseminate health projections or use them to make policy must be attentive to avoiding bias, dismantling feedback loops, and looking out for misdirection. Without critical and collaborative vigilance about their effects, interrogation of the assumptions they embed, and efforts to imagine alternative—even surprising—possibilities, health-related predictive tools may create undesirable futures rather than avert them.

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Conflicts of interest

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