Journal of Critical Public Health, **Online First (2026)**

Research Paper

'Imaginative captivity' in modeling future maternal and child health outcomes: A critical analysis of the Lives Saved Tool (LiST)

Iveoma Udevi-Aruevoru[1*]

[1] Faculty of Health Sciences, Simon Fraser University, Burnaby, British Columbia, Canada
* Corresponding author: Iveoma Udevi-Aruevoru, iveomau@sfu.ca

The Lives Saved Tool (LiST) is a modeling software used to predict the impact of health interventions on maternal and child health and mortality in low-resource settings. LiST is more than a predictive software for maternal and child health. It is also a governance mechanism, organizing maternal and child health actors – including policy makers, program planners, NGOs, and researchers – to address maternal and child health according to donors' preferences for cost-effective, standalone technical interventions. In this paper, I trace the history of LiST – from its early days as a series of spreadsheets created for a special issue in The Lancet by the Bellagio Group, a cohort of child survival researchers concerned about excess child mortality – to show how and why LiST data and frameworks narrow the scope of interventions considered appropriate for maternal and child health care in low-resource settings. LiST's data and governance effects produce an imaginative captivity that sidelines other ways of knowing about maternal and child health in poor countries, circumscribing a fuller range of problem solving – such as listening to mothers, children, and local health care providers, and attending to the cultural, social and political economy factors of health – thereby limiting options for maternal and child health futures.

Introduction

What practices are conducive to bringing forth desirable future maternal and child health (MCH) outcomes? Many global health experts claim that evidence-based priority setting is necessary to shape health care in low-resource settings. Priority setting tools, like computer-based models, are said to lead to improved health outcomes because they enable transparent, rational, and evidence-based decision-making processes (Rudan et al. 2010), qualities that are supposedly absent in many low-resource settings.

In this paper, I examine a priority setting tool preferred by many global health organizations: The Lives Saved Tool (LiST). LiST is a modelling software that uses epidemiological and demographic data to algorithmically predict how scaling up MCH interventions will decrease deaths caused by common maternal and child diseases in resource-scarce settings. LiST was born of a widespread concern that far too many mothers and children are dying of preventable diseases. A team of researchers at Johns Hopkins

University, guided by the World Health Organization (WHO) and UNICEF, along with start-up funding from the Bill and Melinda Gates Foundation, developed LiST in 2003. LiST, they say, addresses the perception that, in low-resource settings, 'many programs are planned and implemented without a clear understanding of the impact [project planners] can expect from their program' (Walker & Tam 2022, p. 18). LiST aims to fix concerns that MCH priority setting and decision-making in low-resource settings is not sufficiently rational. The researchers that developed LiST conceived of the model 'as a way to quantify the potential effectiveness of an intervention' (Walker et al. 2013, p. 1). Promotional and educational material, and journal articles about LiST, claim that LiST does this by drawing from 'high quality' data to produce estimates about intervention effectiveness that are evidence-based. LiST's baseline research is widely seen as objective. One LiST webinar declared, LiST 'provides a sturdy foundation on which to justify why you want to focus on the interventions that you choose' (LivesSavedTool 2018b, 6:28).

In the field of global health, quantitative evidence-based practices, like mathematical modeling, satisfy demands for incontrovertible proof that a proposed intervention will be effective particularly in contexts where resources are scarce, and donors are providing the funds. Proponents of evidence-based priority setting hold that LiST and other quantitative tools provide a degree of certainty for MCH actors – i.e., donors, local policy makers, program planners, NGOs, and researchers – that funds will be directed towards the most (cost) effective interventions (e.g., Rudan et al. 2010). As such, MCH actors use tools like LiST to predict which intervention, or combination of interventions, will have the greatest impact on mortality. Much has been written about LiST's utility for planning and evaluating health programs in low- and middle-income countries (Rudan et al. 2010, Winfrey et al. 2011, Walker et al. 2013, Walker & Tam 2022). Even more has been written about the potential for certain interventions to reduce mortality rates as evidenced by LiST (e.g., Chola et al. 2015, Lungiswa et al. 2017, Nove et al. 2021). A single tool or technology can be deployed for multiple tasks and often accomplishes more than one goal (Wendland 2022). In this way, LiST appears to accomplish its designers' aim of enabling users to plan evidence-based, life-saving MCH interventions. But what else does LiST accomplish?

Modelling tools like LiST have significant governance effects. This is because, as scholars Rhodes and Lancaster observe, 'projections, as with other metrics, work to standardize and stabilise the objects of health, population and future in particular ways' (2020, p. 178). Indeed, LiST is used by numerous institutions including the Gates Foundation, the US Agency for International Development (USAID), the UK Department for International Development, and the WHO for monitoring and evaluation purposes. Local ministries of health use LiST to decide on funding allocations. NGOs use LiST to bolster their MCH advocacy efforts (Stegmuller et al. 2017).

The future is at once malleable, open to multiple trajectories, and contingent on which imaginaries – i.e., collective visions of the future – become authoritative (Oomen et al. 2021). Quantitative priority setting tools render future risks and uncertainty more concrete and amenable to intervention. These tools, then, communicate authoritative visions of the future, prescribing how certain futures can be attained – or avoided – if people and actions are organized accordingly. In this paper, I bring together insights from anthropology, sociology, and science and technology studies, to offer an example of how quantitative priority setting tools are important mechanisms for global MCH governance. Specifically, I show that LiST organizes MCH actors in ways that align with hegemonic ideals of technical rationality – that is, the privileging of forms of reasoning and accounting based on quantitative knowledge because numbers hold elevated status as objective, apolitical, and therefore truthful reflections of the empirical world (Adams 2016, Merry 2016).

To be sure, technical and rational priority setting is a good thing. But what kinds of MCH futures are possible when modeling extrapolates from past data to prescribe the present-day actions necessary to achieve certain hoped-for future outcomes? Taking inspiration from anthropologist Merry's (2016) concept of data inertia, which I explain in greater detail below, I show that LiST's reliance on past data about intervention effectiveness coupled with its inability to measure the convergent complexities of resource flows, infrastructure, and the people doing the care work, have resulted in the interventions included in the model being too narrow in scope. This fact, together with its governance effects, means that LiST helps entrench particular, top-down, donor-centric visions of what appropriate MCH care and intervention consists of in low-resource settings.

Tools like LiST are growing in number and popularity (Erikson & Udevi-Aruevoru 2023). But there are problems resulting from their design and habituated use. Due to data inertia, LiST-modeled MCH futures are not varied or open-ended. Rather, they are circumscribed by data from and about the past. Alternative visions for creating desirable MCH futures are sidelined owing to what Prainsack (2022) calls 'imaginative captivity' which leads to the inability to envision differently and act towards building better, alternative, and more capacious MCH futures. Imaginative captivity lays bare how taken-for-granted modeling practices constrain possible MCH futures by shaping what is considered appropriate MCH care in low-resource settings and thus have material effects on women and children's lives.

In what follows, I unfold how LiST came to be. Examining the history of LiST's development reveals how the model itself shapes how MCH futures come into being while ignoring essential and more timely inputs. Next, I explore the particular ways in which LiST organizes actors around MCH in low-resource settings, before moving on to a discussion of how LiST has the potential to lead to circumscribed MCH futures by strengthening the ongoing 'verticality' of MCH care in low-resource settings (Roalkvam & McNeill 2016).

Analytical Framework

Faith that the LiST model produces more certainty about what will happen in the future from its prescribed interventions is emblematic of our current moment in which we are constantly anticipating, oriented towards the future. As Adams et al. (2009) observe, the pervasiveness of anticipatory regimes means that 'the future increasingly not only defines the present but also creates material trajectories of life that unfold as anticipated by […] speculative processes' (p. 248). With modeling, a standard method of anticipating, both the future *and the past* are brought to bear on the present, prescribing how to organize ourselves for the hoped-for futures modeling practices predict.

To understand how LiST-mediated MCH futures become circumscribed, Merry's (2016) concept of data inertia is constructive. Because collecting new data is expensive, people doing measurement work often rely on or repurpose existing data. As these existing data limit what can be measured, measurement systems tend to follow and build on past work and established knowledge (Merry 2016). In conceptualizing data inertia, Merry largely focuses on its knowledge effects. However, because data and data practices convey knowledge, which is then translated into action, data have an agentic quality to them – that is, they are 'material prompts for how to act' (Dumit & de Laet 2014, p. 74). To that end, my analysis of LiST builds upon and extends the concept of data inertia by unfolding its performative aspects in addition to its knowledge effects. If data inertia results in a tendency to follow established knowledge, my analysis of LiST shows that data inertia also results in a tendency to follow well-trodden paths. In other words, LiST is enacted as both a prospect and constraint, organizing present day actions and, in turn, future outcomes.

To explore some of the potential consequences of LiST for MCH futures, I bring Merry's data inertia concept into conversation with Barbara Prainsack's work on 'non-imagination.' Why is it that people fail to act towards creating desirable alternative futures? Prainsack (2022) attributes this in part to non-imagination, that is, the absence of alternative visions for, or expectations about, better futures. The problem is that some imaginaries become inconceivable within particular hegemonies, that is, ways of doing and thinking, like those encouraged by LiST. Prainsack conceptualizes 'imaginative captivity' as those deep-seated societal systems of practices that foreclose other 'methods of appreciating, seeing, and acting' in the world (2022, p. 19). Similarly, LiST helps to entrench existing knowledge and evidence about global MCH intervention effectiveness, marginalizing alternative and more expansive MCH futures in low-resource settings.

Methods

The analysis presented in this paper emerges from my master's thesis project that aimed to examine why LiST, as an instantiation of the growing use of modeling software tools for global MCH finance decision-making, has become a preferred standard for MCH planning in low-resource settings. To accomplish this, I relied on document analysis. Drawing on anthropological theorizing of documents, I considered documents to be more than innocuous items that contain information (Pigg et al. 2018). Rather, documents are 'paradigmatic artifacts of modern knowledge practices' (Riles 2006, p. 2). To study documents is to study what the producers of documents know or what they want people who engage with the documents to know (Riles 2006). Within this framework, I considered the documents about LiST as careful articulations of the producers' stances on LiST. Thus, I analyzed the documents for what they could reveal about LiST and the actors involved in its creation, promotion, and dissemination (Davis & Craven 2016).

In May 2023, I conducted a keyword search of the PubMed and Scopus databases to find articles containing the exact phrase 'lives saved tool.' The keyword search produced an initial result of 219 articles. The article abstracts were manually read and filtered to determine whether an article articulated viewpoints about LiST and its utility for planning, monitoring and evaluation, and advocacy. Articles about the technical aspects of LiST (i.e., an in-depth description of its theoretical and statistical modeling approach) were excluded. Articles about using LiST for validation purposes (i.e., comparing the validity of LiST's computations against empirical observations and measurements) were also excluded, as these articles generally did not comment on LiST's utility. Furthermore, I systematically searched Google (using the keyword 'lives saved tool') and the LiST website (www.livessavedtool.org) for additional documents describing perceptions of LiST's utility. The final count of documents analysed was 18. The reviewed documents included instruction manuals, webpages, PowerPoint presentations, and online pamphlets describing and promoting LiST, as well as empirical articles that reported stakeholders' views about LiST. When I later became interested in exploring how LiST helps bring certain MCH futures into being, I closely reviewed additional webinars, instructional YouTube videos, journal articles and supplements published by the LiST team outlining the LiST model's methodological framework and assumptions.

To analyze the documents, I applied thematic analysis as outlined by Braun and Clarke (2006, 2021). Per Braun and Clarke (2021), thematic analysis involves six iterative steps: familiarization with the data; coding the data; generating initial themes from the codes; reviewing themes; refining, defining and naming themes; and writing up the results. Braun and Clarke emphasize a reflexive approach to thematic analysis wherein a researcher's subjectivity is viewed as an instrument. Reflexivity allows for an awareness of how the researcher's positionality, experience, values, and decision-making influence the data interpretation and theme generation (Braun & Clarke 2006, Morgan 2021). Furthermore, thematic analysis was chosen for its flexibility, as it allows for the application of both inductive and deductive coding (Braun & Clarke 2021). I used a qualitative data analysis software, NVivo, to code the 18 documents. I employed both inductive coding and deductive coding – specifically, codes informed by themes in the anthropology and sociology literature on metrics and quantification in global health (e.g., 'accountability' and 'evidence-based') (Bernard 2006). I coded at both the descriptive (explicit or overt) and latent (implicit or contextual) levels to create codes and then generate themes.

Past As Blueprint: The Making of the Lives Saved Tool

In 2003, a group of child health scientists and policy makers convened in Bellagio, Italy for the Lancet Child Survival series, a series of papers making the case for increasing funding for child survival interventions. This group of experts, the Bellagio Child Survival Study Group (Bellagio Group), were concerned about the lack of attention on the high rates of child mortality, over 10 million per year at the time, from preventable causes, including diarrhea, malaria, and measles, in low- and middle-income countries (Victora 2010).

The Bellagio Group wanted to estimate the number of child deaths that could be prevented by increasing coverage – i.e., the proportion of a population in need of a health intervention that actually receives it – of then available preventive and therapeutic child survival interventions (Jones et al. 2003). From their review of the existing child survival research, they created a series of spreadsheets that included 23 interventions deemed both feasible to implement and scalable in low-resource community settings (Walker & Tam 2022).

What made an intervention 'feasible' to implement and scale up to high levels of population coverage was not clearly explained in the papers. While the group of experts granted that 'what is feasible [...] varies widely even among low-income countries,' they later on, in a parenthetical manner, wrote that the model 'excluded some interventions for which there is sufficient evidence of effect, but that are only feasible for implementation in countries with higher levels of human, health-system, and financial resources' (Jones et al. 2003, p. 69). The Bellagio Group's nebulous articulation of feasibility evokes a deeply-embedded concept in global health: 'appropriate technologies.' Appropriate technologies are interventions that donors and policy makers deem suitable for certain people, in certain places, largely as a function of cost, implying that more expensive interventions are unsuitable (Wendland 2022).

Meanwhile, the estimates of intervention effectiveness were obtained from 'existing research reports and systematic reviews,' and from the experiential knowledge of members of the Bellagio Group (Jones et al. 2003, p. 65). To be included in this early proto-LiST model, interventions had to show either sufficient or limited evidence of reducing deaths from the then major causes of under-five mortality. The experts sought sufficient evidence of intervention effectiveness, meaning they wanted direct causal claims. They wanted to see causal relationships between interventions and reductions in child mortality in low-resource countries. Limited evidence of effect meant that 'an effect was possible, but available data were not sufficient to establish a causal relationship' because of conflicting evidence from the reviewed studies or there were not enough studies to generalize the findings, among other reasons (Jones et al. 2003, p. 66). As an example, among the 23 preventive and treatment-based interventions incorporated in this early model was oral rehydration therapy, which the Bellagio Group determined had sufficient evidence of effect on reducing child deaths caused by diarrhea. The early model also included vitamin A, which the Bellagio Group judged had limited evidence of effect on reducing child mortality caused by measles (Jones et al. 2003, p. 66).

The Bellagio Group then estimated the existing coverage levels of the 23 interventions in the 42 low- and middle-income countries with the highest rates of child mortality. Based on data from UNICEF and other sources, they estimated that coverage of most of the 23 interventions was below 50% in the majority of the 42 countries. After inserting this data into the spreadsheets, their model estimated that if the coverage of all 23 interventions was set at universal (i.e., high) levels in the 42 low-resource countries, 63% of child deaths could be prevented (Jones et al. 2003). The Bellagio Group concluded that achieving the Millenium Development Goal 4 – reducing child mortality by two-thirds by 2015 – was achievable (Walker & Tam 2022). Thus, the experts argued, a major impediment to reducing child mortality was that the available interventions were not being implemented, despite the knowledge and the available tools to do so (Jones et al. 2003). This proto-model, sometimes referred to as the 'Bellagio spreadsheets,' is said to have helped '[place] child survival back on the international agenda' (Victora 2010, p. i1).

This early model also laid the groundwork for what would eventually become LiST. Whereas the original model was a spreadsheet that focused on child survival, LiST has evolved into a free, publicly available computer application, and more recently a web-based version, and has expanded to include additional health outcomes such as maternal health, stillbirths, and neonatal health. The number of interventions has also grown from 23 community-based child survival interventions to more than 80 reproductive, maternal, newborn, child health and nutrition interventions, many of which are facility-based.

The development of LiST from a simple spreadsheet model to a software tool exemplifies data inertia. The Bellagio Group met at the turn of the millennium to create the spreadsheet model using data from systematic reviews and research reports that stretch back even further – most of the systematic reviews were published in the 1990s. More than 20 years later, the model's base framework of feasible and scalable interventions is still being used today. The initial model's methods and assumptions about child survival, which 'linked levels of intervention coverage with reductions in cause-specific child mortality' (Walker & Tam 2022, p. 17), were carried over to the LiST model. Like its precursor, LiST is also a linear model, meaning that there is a straight-line relationship between two variables: a change in one variable is met with a corresponding change in another variable. Here, LiST is coded to presume that changes in mortality result from changes in intervention coverage levels. In the LiST model, like with its predecessor, each intervention is tied to a specific cause of death. For example, the intervention, administering magnesium sulfate for pre-eclampsia, is linked to a cause of maternal death, hypertensive disorders.

Merry notes that 'measurement generally builds on previous models and approaches, refining or expanding them or correcting their recognized problems' (2016, p. 6). The LiST creators, a group of epidemiologists, statisticians, and research scientists at Johns Hopkins University distinct from the Bellagio Group, describe LiST as a refinement of the early model's methods and assumptions (Walker et al. 2013, Walker & Tam 2022). For example, unlike its Bellagio Group predecessor, risk factors are now included in the model because not all interventions have a direct impact on mortality. The LiST developers rationalize that some interventions directly impact a risk factor and then the risk factor directly impacts mortality. For example, the intervention iron supplementation in pregnancy is connected to the risk factor maternal anemia which is a risk factor for maternal mortality (LivesSavedTool 2018a). Furthermore, the original Bellagio Group model only considered biomedical and technical interventions that targeted the downstream determinants of child mortality – i.e., factors that directly affect health – and that can be delivered through the health sector (Jones et al. 2003), leaving out social and political economy factors of health. This approach was carried over to LiST. The LiST model's sole inclusion of biomedical and technical interventions is a function of data inertia: past knowledge and theories about suitable MCH interventions carry over and build upon in the present.

LiST focuses on biomedical and technical interventions in ways that misdirect attention away from alternative non-biomedical and non-technical yet potentially effective interventions for addressing MCH (Peeters Grietens et al. 2022, Wendland 2026, in press). As Kingori and Gerrets argue, '[the] ability to misdirect attention, to decide where an audience looks, is a manifestation of power' (2019, p. 387). LiST's particular method of anticipating MCH futures, modeling, is embedded in the belief that evidence-based practices are among the most reliable and effective means for achieving improved MCH outcomes and thus desirable MCH futures. That LiST only includes technical and biomedical interventions is both in keeping with, and a function of, the ongoing technocratic narrowing in global health, itself a consequence of the emphasis on evidence-based medicine in global public health (Storeng & Béhague 2014), at the expense of factoring in the custom, culture, social and political realities of any given locale.

The use of LiST is mandated in certain instances, to plan, monitor, and evaluate MCH projects. This, in turn, means that LiST sets the frame within which MCH actors in low-resource settings, particularly those that depend on external funding, are encouraged to plan and work towards achieving hoped-for MCH outcomes. As such, LiST has significant governance effects. In the next section I explore the particular ways in which LiST governs actors around MCH in low-resource settings, and the implications for MCH futures.

Chasing Donors, Tuning Out Mothers and Children

The authority of and trust in quantitative forms of reasoning (Porter 1995) help explain why the use of LiST and other quantitative priority setting tools is growing and often expected among MCH actors.

Anthropological research has shown that the emphasis on numbers and evidence-based practices has transformed what is considered a 'successful' and thus fundable health intervention (e.g., Adams 2010, Tichenor 2017). For instance, writing about efforts to reduce maternal mortality in Tibet, Adams (2005) found that a proposed intervention was scrapped because it could not be shown to be statistically significant. In short, because the proposed intervention could not be quantified, it was rendered illegible in a global health landscape that values numbers as a signal for invest-ability. Only those interventions that could be evaluated via a randomized control trial and demonstrate sufficient statistical significance, for example, were considered legitimate and thus worthy of funding (Adams 2010). Crucially, interventions that can be assessed for effectiveness in this manner tend to be technical, individual-level fixes and cheaper to implement compared to projects that attend to the broader structural conditions that affect health and wellbeing and typically require long-term investment. This aligns with donor preferences and many global health initiatives which, in many instances, have embraced targeted technical and biomedical interventions, favouring them for their measurable outcomes (Storeng 2014). In this way, priority-setting tools like LiST are important governance mechanisms since they furnish the kinds of evidence valued by global MCH actors.

Indeed, one notable governance effect of LiST is that its use can shift attention towards donors rather than listening to women and children, and local health care practitioners because of its utility for gaining recognition and buy-in from donors. A review of the ways and reasons LiST is used found that MCH actors frequently use LiST for preparing proposals for MCH projects. The review noted that modeling was an important part of the proposal writing process because 'donors prefer that implementers model the possible impact of their program' (Stegmuller et al. 2017, p. 147). Furthermore, users reported that LiST is useful for gaining donor support because 'most donors seek to identify some cost-effectiveness metric [and] "lives saved" is a tangible metric that enables donors to understand the impact of their investments' (Stegmuller et al. 2017, p. 147). MCH actors use LiST to convince funders that their proposed plans for MCH are sufficiently rational and transparent. LiST is used to speak to donors in a concrete language they can understand: cost-effectiveness and the number of lives saved. Indeed, LiST provides a rationale for them that aligns with a dominant objective and ethos of contemporary global health, as endorsed by many of its powerful players: investments in health should provide value for money, namely in terms of the number of lives saved (Roalkvam & McNeill 2016, p. 73).

The strategic use of quantitative evidence to gain recognition for MCH causes is not new. Storeng and Béhague (2014) detail how many advocates for the Safe Motherhood Initiative (SMI) use 'evidence-based advocacy' – the use of quantitative evidence and cost-effectiveness data to persuade and procure investment in maternal health. While many of their interlocutors felt ambivalent about the need to use quantitative evidence rather than feminist grounds and moral claims to bolster support for SMI, partly because it resulted in the technocratic narrowing of policies for SMI, they still recognized 'playing the numbers game' as a viable strategy for obtaining funding and support from donors.

Old Data and Projected Futures

While evidence-based advocacy may be a viable strategy for securing donor funding, priority-setting tools like LiST can maintain the power imbalances that shape so much of the MCH policy space in resource-scarce settings. Specifically, the privileging of LiST, and particularly the kinds of evidence it uses and generates, helps ensure that the use of such quantitative priority setting tools becomes habitual because repetition stabilizes. It is the kind of inertia that results in LiST increasingly becoming seen as an acceptable, common-sense tool for shaping MCH care. Donors' preferences end up demarcating the bounds within which MCH policy makers in resource-poor countries are encouraged to plan for MCH, sidelining alternative possibilities which typically fail to gain the recognition of powerful donors, and LiST helps to accomplish this.

This last point is particularly salient given that much of the data LiST draws on to make its projections are known to contain uncertainties (Fischer Walker & Walker 2014), making its projections quite 'wobbly' (Wendland 2016, p. 68). The allure of LiST is that it is said to be a robust, evidence-based model. Yet, a close read of LiST's baseline intervention coverage data reveals some limitations. To illustrate, in May 2025 the web-based version of LiST, 'LiST Online,' showed that the default coverage level of insecticide-treated mosquito nets – a method of preventing malaria – in Nigeria was 51.5%. While users can choose to input their own data if they have better or more recent data, by default LiST is loaded with baseline data inputs. For Nigeria, most of the baseline intervention coverage data are sourced from Demographic and Health Surveys (DHS), Multiple Indicator Cluster Surveys (MICS), and other nationally-representative household surveys. These surveys collect data on health and intervention coverage in more than 90 low- and middle-income countries. (Readers can refer to Bryce et al. (2013) for an overview of the DHS and MICS as well as an analysis of their strengths and limitations.)

Per USAID and UNICEF, the founders of the DHS and MICS programs, respectively, these household surveys produce high-quality, statistically sound and comparable estimates. That these data are loaded into LiST by default is one reason the LiST team claims the model provides 'a sturdy foundation' for MCH priority setting. Yet, these surveys are not updated frequently. The DHS, for instance, are administered every five years. This means that when it comes to the estimates of intervention coverage level, such as the use of insecticide-treated nets, LiST is using data that is at least five years old – and conceivably much older than that given the time it takes to process these surveys. The baseline coverage data of insecticide-treated nets in Nigeria, for example, was sourced from the 2018 DHS. Also of note, a known limitation of the household surveys is that they do not yield highly accurate coverage measures of key interventions for MCH (Bryce et al. 2013, Fischer Walker & Walker 2014). All of this raises questions about the robustness of the LiST model's projections.

The LiST team acknowledges that 'LiST outputs are only as valid as the input data on which they are based' (Walker & Friberg 2017, p. 1). This is true of all models. Social science scholarship on the production of global maternal health data – many of LiST's inputs – have shown the data to be rife with uncertainty (Erikson 2012, Wendland 2016). Data are manipulated and misreported, health phenomena are sometimes misclassified or undercounted due to failing memories, in response to political pressure, or simply for self-preservation (e.g., Kingori & Gerrets 2016, Oni-Orisan 2016, Suh 2021, Varley 2023). The statisticians, epidemiologists, demographers, and other researchers who designed LiST recognize the data LiST relies on may be inadequate (e.g., Fox et al. 2011, Walker et al. 2013). Nevertheless, they maintain that LiST is integral to the global health toolkit. LiST's outputs are supposed to be predictions for the future, yet they are based on imperfect data. How useful can these predictions really be?

To be clear, by getting into the weeds of some of LiST's baseline intervention coverage data, I am not necessarily arguing for 'better' or more accurate data. Rather, my point is that using LiST appears to be a clear example of 'using something is better than nothing.' In other words, despite its inaccuracies, it seems that because LiST can show donors what will 'work' to improve MCH outcomes and achieve certain hoped-for futures, based on valued rational, objective, and transparent evidence, any shortcomings of the LiST model's inputs and outputs can be overlooked. This is also not to say that the interventions in the LiST model are wholly ineffective or that they should not be implemented. Rather, the sole focus on these interventions means that more expansive methods of improving MCH, starting with better listening to women, children, and caregivers, and attending to the local social and political contexts, are sidelined. The truthiness of LiST's projections mobilizes action and resources in ways that are donor-centric, towards technical interventions.

As Storeng and Béhague (2014) argue, 'responding to donors' demands for numbers diverts attention from building sustainable and locally relevant health systems' (pp. 271-272). It also diverts attention from MCH *care*. With LiST, this misdirection enables forms of governance where MCH actors in low-resource countries focus on donors' expectations. As research on global health data has shown, how a problem is framed shapes its imagined solutions (Wendland 2022). If problems are viewed through the lens of numbers, the possibilities and recommendations for addressing said problems will be imagined correspondingly. For donors, beyond being a predictive tool, LiST is used to exercise power by framing how MCH problems are conceptualized and by shaping their possible solutions (Suh 2019). I turn now to discuss how the ongoing use of LiST and trust in the model, alongside its focus on a narrow set of biomedical and technical interventions, mean that the possibilities for addressing MCH challenges in resource-scarce settings, and thus MCH futures, are circumscribed.

Circumscribed Maternal and Child Health Futures

Sociologists have argued that standards, central to modern life, represent and prescribe particular interests, priorities, ethics, and values (Lampland & Star 2009, p. 8). Over time, as standards are implemented and enforced, they form tacit knowledge and come to be seen as common sense. Once standards are put in place, they have significant inertia making it difficult to contest and change them (Bowker & Star 1999, Timmermans & Berg 2003). I consider LiST as having the potential to operate similarly by helping to standardize and reinforce prevailing perceptions and evidence that certain narrow, technical interventions are the most effective for improving MCH in resource-scarce settings and simply need to be scaled up.

In 2003, when the Bellagio group created the spreadsheets that would later form the basis of LiST, their goal was to estimate the impact of translating existing knowledge about proven child health interventions into effective action. In their view, their spreadsheet model clearly showed that high rates of child mortality were not due to a lack of knowledge about what works to prevent child deaths. Rather, it was that then available proven child survival interventions – narrowly defined as 'biological agent[s] or action[s] intended to reduce morbidity or mortality' (Jones et al. 2003, p. 65) – were not being scaled up. This is consistent with anthropologist Vincanne Adams' observation that global health practitioners 'envision a world in which interventions can be mapped out as problems of scale and measurement […] rather than as problems of custom, culture, or national political will' (2016, p. 6). Scholars have argued that evidence-based technical interventions, suffused with a kind of magic as they are imagined as having the capacity to directly and effectively tackle intractable health problems, have reduced the scope of global health work by conceiving health issues as separable from their social contexts (Yates-Doerr et al. 2023). As the use of LiST continues to grow – to gain recognition and buy-in from donors – and because of data inertia, the focus on narrowly defined interventions and scalability is reinforced. It may also become increasingly difficult to contest this framework or to include other knowledge systems and frameworks that are less amenable to statistical evaluation (Merry 2016). In helping to make technical MCH interventions normative, LiST may also make it possible to forget that ways of improving MCH might be imagined differently. LiST, as a blueprint for building MCH futures, is too limited in scope because of its dependence on existing data and frames for addressing MCH in resource-scare settings.

My contention that LiST can lead to circumscribed MCH futures is also based on the model's focus on feasibility. Feasibility seems to be code for the concept of 'appropriate technology' which medical anthropologists have long critiqued as a cover for injustice since it is typically poor people who get 'appropriate' interventions (Farmer 2001). As mentioned, LiST only includes interventions that are 'feasible' to implement in low- and middle-income settings (LivesSavedTool 2018c, 9:45), meaning that the range of LiST's interventions is limited. In the original Bellagio spreadsheets, the concept of narrowly targeted interventions was entwined with the idea of feasibility, with repeated references to interventions capable of being delivered at 'high levels of population coverage' (Jones et al. 2003, p. 66). Although, it is a carryover of the Bellagio spreadsheets, the LiST team does not explain what feasible means. We are left to assume that it is a function of scalability in addition to infrastructural and financial resources, since the tool is designed for use in poor countries and the included interventions are standalone. With LiST, it seems that feasibility – and by extension cost – operates as a limiting factor, playing a significant role in shaping what kinds of interventions are considered appropriate for improving MCH care within the confines of resource scarcity and donor-funded initiatives. LiST's ability to model only those interventions that are technical and feasible for low-income countries necessarily constrains the scope of possible MCH futures. Exhortations to use LiST to plan for MCH in low-resource settings reflect the workings of imaginative captivity. Through data inertia, LiST entrenches this narrow way of thinking about and working towards building MCH futures. Conversely, MCH futures that call for much more than vertical approaches to achieving health and wellbeing are cordoned off.

Conclusion

As a tool for strategic planning and advocacy for MCH in low-resource settings, LiST claims to model a desirable future that can be attained if certain interventions are carried out in the present. In this paper, I have offered a more skeptical view of the tool, arguing that, because of data inertia, and the resultant narrowed scope of interventions included in the LiST model, the possibilities for achieving desirable MCH futures are circumscribed. This is not particularly surprising given the inherent inaccuracies of mathematical modeling: 'assumptions are limiting, and available data rarely matches the known need for data' (Roberton et al. 2017, p. 156). Given the poor track record of vertical health approaches (Packard 2016), LiST is not a tool that is likely to save maximal lives, certainly not in the way that investments in primary care do. LiST's key features – the narrow scope of possible interventions, the emphasis on undefined 'feasibility' – all but ensure that any effect it has will be limited. Yet, this has not stopped LiST from reaching an inescapable presence among global MCH health organizations because of its utility in gaining recognition from donors. Despite its known limitations, the tool organizes MCH actors to target MCH in limited, vertical health approaches. LiST, then, might more appropriately be conceived of as a tool for mobilizing buy-in from donors than saving lives.

My analysis of LiST expands the concept of data inertia to highlight how the knowledge derived from existing data act as a blueprint that shapes both the present and the future. Here, data inertia shows there is potential for LiST to marginalize alternative evidence and visions for enacting desirable MCH futures as it entrenches a technological approach to conceptualizing and addressing MCH and makes it difficult to incorporate new forms of knowledge and experiences that resist reductionism. What kinds of imaginations are needed to create desirable MCH futures? What kinds of tools and what sets of experts could make imaginative liberation instead of imaginative captivity? LiST's interventions focus on a particular point of time and space: the community and the clinic or hospital for its community-based and facility-based interventions, respectively. But what of the period before and after, when women and children leave the clinic and return to their material and structural living conditions? LiST's limited focus on feasible interventions misdirects attention away from this important context and helps strengthen the ongoing 'verticality' of global public health initiatives for MCH care in low-resource settings (Roalkvam & McNeill 2016). Foregrounding imaginations and knowledge that channel attention to efforts to address the contextual factors that shape health and wellbeing, are one way to ensure that more capacious MCH futures are brought into being rather than foreclosed.

Acknowledgments

Many thanks to attendees of the Desirable/Undesirable Futures workshop and members of the Personalized Medicine in the Welfare State research group at the University of Copenhagen for their invaluable feedback on earlier versions of this paper. Thanks also to the anonymous reviewers, whose careful comments helped improve the quality of this paper. This paper draws on research supported by the Social Sciences and Humanities Research Council of Canada Graduate Scholarship-Master's award (Reference Number 207-2021-2022-Q2-00924).

Conflicts of interest

The author declares no conflicts of interest.

ORCiD ID

Iveoma Udevi-Aruevoru https://orcid.org/0009-0006-3758-2093

References

Adams, V. (2005) Saving Tibet? An inquiry into modernity, lies, truths, and beliefs. *Medical Anthropology, 24*(1), 71-110. https://doi.org/10.1080/01459740590905651

Adams, V. (2010) Against global health? Arbitrating science, non-science, and nonsense through health. In J. M. Metzl & A. Kirkland (Eds.), *Against health: How health became the new morality* (pp. 40–60). NYU Press.

Adams, V. (Ed.) (2016) *Metrics: What counts in global health*. Duke University Press.

Adams, V., Murphy, M., & Clarke, A. E. (2009) Anticipation: Technoscience, life, affect, temporality. *Subjectivity, 28*(1), 246–265. https://doi.org/10.1057/sub.2009.18

Bernard, H. R. (2006) *Research methods in anthropology: Qualitative and quantitative approaches*. AltaMira Press.

Bowker, G. C., & Star, S. L. (1999) *Sorting things out: Classification and its consequences*. MIT Press.

Braun, V., & Clarke, V. (2006) Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

Braun, V., & Clarke, V. (2021) Can I use TA? Should I use TA? Should I not use TA? Comparing reflexive thematic analysis and other pattern-based qualitative analytic approaches. *Counselling & Psychotherapy Research, 21*(1), 37-47. https://doi.org/10.1002/capr.12360

Bryce, J., Arnold, F., Blanc, A., Hancioglu, A., Newby, H., Requejo, J., & Wardlaw, T. (2013) Measuring coverage in MNCH: New findings, new strategies, and recommendations for action. *PLoS Medicine, 10*(5), 1-9. https://doi.org/10.1371/journal.pmed.1001423

Chola, L., McGee, S., Tugendhaft, A., Buchmann, E., & Hofman, K. (2015) Scaling up family planning to reduce maternal and child mortality: The potential costs and benefits of modern contraceptive use in South Africa. *PLOS ONE, 10*(6), 1-16. https://doi.org/10.1371/journal.pone.0130077

Davis, D.-A., & Craven, C. (2016) *Feminist ethnography: Thinking through methodologies, challenges, and possibilities*. Rowman & Littlefield Publishers.

Dumit, J., & de Laet, M. (2014) Curves to bodies: The material life of graphs. In D. L. Kleinman & K. Moore (Eds.), *Routledge handbook of science, technology, and society* (pp. 71–89). Routledge.

Erikson, S. L. (2012) Global health business: The production and performativity of statistics in Sierra Leone and Germany. *Medical Anthropology, 31*(4), 367–384. https://doi.org/10.1080/01459740.2011.621908

Erikson, S., & Udevi-Aruevoru, I. (2023) The future of reproductive health financing. In C. C. Van Hollen & N. Appleton (Eds.), *A Companion to the anthropology of reproductive medicine and technology* (pp. 153-167). John Wiley & Sons.

Farmer, P. (2001) *Infections and inequalities: The modern plagues*. University of California Press.

Fischer Walker, C. L., & Walker, N. (2014) The Lives Saved Tool (LiST) as a model for diarrhea mortality reduction. *BMC Medicine, 12*(70), 1-13. https://doi.org/10.1186/1741-7015-12-70

Fox, M. J., Martorell, R., van den Broek, N., & Walker, N. (2011) Assumptions and methods in the Lives Saved Tool (LiST). *BMC Public Health, 11*(3), I1. https://doi.org/10.1186/1471-2458-11-S3-I1

Jones, G., Steketee, R. W., Black, R. E., Bhutta, Z. A., & Morris, S. S. (2003) How many child deaths can we prevent this year? *The Lancet, 362*(9377), 65–71. https://doi.org/10.1016/S0140-6736(03)13811-1

Kingori, P., & Gerrets, R. (2016) Morals, morale and motivations in data fabrication: Medical research fieldworkers views and practices in two Sub-Saharan African contexts. *Social Science & Medicine, 166*, 150–159. https://doi.org/10.1016/j.socscimed.2016.08.019

Kingori, P., & Gerrets, R. (2019) Why the pseudo matters to global health. *Critical Public Health, 29*(4), 379–389. https://doi.org/10.1080/09581596.2019.1605155

Lampland, M., & Star, S. L. (Eds.) (2009) *Standards and their stories: How quantifying, classifying, and formalizing practices shape everyday life*. Cornell University Press.

LivesSavedTool (2018a, December 5th) *Introduction to LiST #1 - Background and history* [Video]. YouTube. https://www.youtube.com/watch?v=6y54aMS6D0w

LivesSavedTool (2018b, December 5th) *Introduction to LiST #2 - Calculating impact in LiST* [Video]. YouTube. https://www.youtube.com/watch?v=SmFm4tGsXHk

LivesSavedTool (2018c, December 5th) *Introduction to LiST #3 - Multiple impact calculations LiST, advantages and disadvantages* [Video]. YouTube. https://www.youtube.com/watch?v=QtRk-CdHkBI

Lungiswa, L. N., Lumbwe, L. C., Aviva, A. T., & Karen, K. H. (2017) Modelling the cost of community interventions to reduce child mortality in South Africa using the Lives Saved Tool (LiST). *BMJ Open, 7*(8), e011425. https://doi.org/10.1136/bmjopen-2016-011425

Merry, S. E. (2016) *The seductions of quantification: Measuring human rights, gender violence, and sex trafficking*. University of Chicago Press.

Morgan, H. (2021) Conducting a qualitative document analysis. *The Qualitative Report, 27*(1), 64-77. https://doi.org/10.46743/2160-3715/2022.5044

Nove, A., Friberg, I. K., de Bernis, L., McConville, F., Moran, A. C., Najjemba, M., … & Homer, C. S. E. (2021) Potential impact of midwives in preventing and reducing maternal and neonatal mortality and stillbirths: A Lives Saved Tool modelling study. *The Lancet Global Health, 9*(1), e24–e32. https://doi.org/10.1016/S2214-109X(20)30397-1

Oni-Orisan, A. (2016) The obligation to count: The politics of monitoring maternal mortality in Nigeria. In V. Adams (Ed.), *Metrics: What counts in global health* (pp. 82–101). Duke University Press.

Oomen, J., Hoffman, J., & Hajer, M. A. (2021) Techniques of futuring: On how imagined futures become socially performative. *European Journal of Social Theory, 25*(2), 225-251. https://doi.org/10.1177/1368431020988826

Packard, R. M. (2016) *A history of global health: Interventions into the lives of other peoples*. Johns Hopkins University Press.

Peeters Grietens, K., Kingori, P., Friesen, P., Gerrets, R., Douglas-Jones, R., & Kuhn, G. (2022) Misdirection in global health: Creating the illusion of (im)possible alternatives in global health research and practice. *Science & Technology Studies, 35*(2), 2–12. https://doi.org/10.23987/sts.115410

Pigg, S. L., Erikson, S. L., & Inglis, K. (2018) Document/ation: Power, interests, accountabilities. *Anthropologica, 60*(1), 167–177. https://muse.jhu.edu/article/705332

Porter, T. M. (1995) *Trust in numbers: The pursuit of objectivity in science and public life*. Princeton University Press.

Prainsack, B. (2022) The roots of neglect: Towards a sociology of non-imagination. *TECNOSCIENZA Italian Journal of Science & Technology Studies, 13*(2), 13–34. https://doi.org/10.6092/issn.2038-3460/17577

Rhodes, T., & Lancaster, K. (2020) Mathematical models as public troubles in COVID-19 infection control: Following the numbers. *Health Sociology Review, 29*(2), 177–194. https://doi.org/10.1080/14461242.2020.1764376

Riles, A. (2006) *Documents: Artifacts of modern knowledge*. University of Michigan Press.

Roalkvam, S., & McNeill, D. (2016) What counts as progress? The contradictions of global health initiatives. *Forum for Development Studies, 43*(1), 69-88. https://doi.org/10.1080/08039410.2015.1134645

Roberton, T., Litvin, K., Self, A., & Stegmuller, A. R. (2017) All things to all people: Trade-offs in pursuit of an ideal modeling tool for maternal and child health. *BMC Public Health, 17*(S4), 785. https://doi.org/10.1186/s12889-017-4751-4

Rudan, I., Kapiriri, L., Tomlinson, M., Balliet, M., Cohen, B., & Chopra, M. (2010) Evidence-based priority setting for health care and research: Tools to support policy in maternal, neonatal, and child health in Africa. *PLOS Medicine, 7*(7), e1000308. https://doi.org/10.1371/journal.pmed.1000308

Stegmuller, A. R., Self, A., Litvin, K., & Roberton, T. (2017) How is the Lives Saved Tool (LiST) used in the global health community? Results of a mixed-methods LiST user study. *BMC Public Health, 17*(4), 773. https://doi.org/10.1186/s12889-017-4750-5

Storeng, K. T. (2014) The GAVI alliance and the "Gates approach" to health system strengthening. *Global Public Health, 9*(8), 865–879. https://doi.org/10.1080/17441692.2014.940362

Storeng, K. T., & Béhague, D. P. (2014) "Playing the numbers game": Evidence-based advocacy and the technocratic narrowing of the Safe Motherhood Initiative. *Medical Anthropology Quarterly, 28*(2), 260–279. https://doi.org/10.1111/maq.12072

Suh, S. (2019) Metrics of survival: Post-abortion care and reproductive rights in Senegal. *Medical Anthropology, 38*(2), 152–166. https://doi.org/10.1080/01459740.2018.1496333

Suh, S. (2021) *Dying to count: Post-abortion care and global reproductive health politics in Senegal*. Rutgers University Press.

Tichenor, M. (2017) Data performativity, performing health work: Malaria and labor in Senegal. *Medical Anthropology, 36*(5), 436–448. https://doi.org/10.1080/01459740.2017.1316722

Timmermans, S., & Berg, M. (2003) *The gold standard: The challenge of evidence-based medicine and standardization in health care*. Temple University Press.

Varley, E. (2023) Hospital paperworlds: Medical (mis)reporting and maternal health in northern Pakistan. *Medical Anthropology Quarterly, 37*(1), 23–41. https://doi.org/10.1111/maq.12737

Victora, C. G. (2010) Commentary: LiST: Using epidemiology to guide child survival policymaking and programming. *International Journal of Epidemiology, 39*(Supplement 1), i1–i2. https://doi.org/10.1093/ije/dyq044

Walker, N., & Friberg, I. K. (2017) Introduction: Reporting on updates in the scientific basis for the Lives Saved Tool (LiST). *BMC Public Health, 17*(S4), 774. https://doi.org/10.1186/s12889-017-4735-4

Walker, N., & Tam, Y. (2022) The role of modeling in evaluation of maternal and child health programs: Using the Lives Saved Tool to help answer core evaluation questions. *Global Health Action, 15*(sup1), 2006421. https://doi.org/10.1080/16549716.2021.2006421

Walker, N., Tam, Y., & Friberg, I. K. (2013) Overview of the Lives Saved Tool (LiST). *BMC Public Health, 13*(3), S1. https://doi.org/10.1186/1471-2458-13-S3-S1

Wendland, C. L. (2016) Estimating death: A close reading of maternal mortality metrics in Malawi. In V. Adams (Ed.), *Metrics: What counts in global health* (pp. 57–81). Duke University Press.

Wendland, C. L. (2022) *Partial stories: Maternal death from six angles*. University of Chicago Press.

Wendland, C. L. (2026, in press) Predictive tools in maternal health: Making futures for patients and populations. *Journal of Critical Public Health*.

Winfrey, W., McKinnon, R., & Stover, J. (2011) Methods used in the Lives Saved Tool (LiST). *BMC Public Health, 11*(3), S32. https://doi.org/10.1186/1471-2458-11-S3-S32

Yates-Doerr, E., Carruth, L., Lasco, G., & García-Meza, R. (2023) Global health interventions: The military, the magic bullet, the deterministic model—and intervention otherwise. *Annual Review of Anthropology, 52*(1), 187–204. https://doi.org/10.1146/annurev-anthro-041520-093024