Mortality risk information and health-seeking behavior during an epidemic

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In a context where pessimistic survival perceptions have been widespread as a result of the HIV/AIDS epidemic (Fig. 1*A*), we study vaccine uptake and other health behaviors during the recent COVID-19 pandemic. Leveraging a longitudinal cohort study in rural Malawi that has been followed for up to 25 y, we document that a 2017 mortality risk information intervention designed to reduce pessimistic mortality perceptions (Fig. 1*B*) resulted in improved health behavior, including COVID-19 vaccine uptake (Fig. 1*C*). We also report indirect effects for siblings and household members. This was likely the result of a reinforcing process where the intervention triggered engagement with the healthcare system and stronger beliefs in the efficacy of modern biomedical treatments, which led to the adoption of health risk reduction behavior, including vaccine uptake. Our findings suggest that health information interventions focused on survival perceptions can be useful in promoting health behavior and participation in the formal healthcare system, even during health crises—such as the COVID-19 pandemic—that are unanticipated at the time of the intervention. We also note the importance of the intervention design, where establishing rapport, tailoring the content to the local context, and spending time with respondents to convey the information contributed to the salience of the message.

survival risk misperceptions | COVID-19 vaccine uptake | mortality expectations | health information interventions | Malawi

Significance

Pessimistic survival expectations are widespread in countries affected for decades by high disease burdens and repeated epidemics. Providing individuals in these contexts with accurate information about population survival risk can help improve health-seeking behaviors. Multiple pathways contribute to these treatment effects, including an increased engagement with the healthcare system and belief that biomedical treatments are effective.

Devising policies that encourage the adoption of effective health-prevention strategies during unanticipated health crises is of utmost importance. The COVID-19 pandemic presented a global health shock and a rapidly changing epidemiological context in which uncertainty about future health outcomes and ambiguity about effective risk reduction strategies were widespread (1). The development and roll-out of novel vaccines in 2021, such as the mRNA vaccines used in the COVID-19 pandemic, provided an effective tool for vastly reducing the morbidity and mortality of COVID-19. As vaccine availability increased, targeting widespread COVID-19 vaccinations as a prevention strategy was critical, particularly in low-income countries (LICs) where overburdened health systems had limited ability to care for and treat individuals experiencing severe illness from COVID-19. Despite this importance, vaccine uptake often fell short of goals needed to reach herd immunization. The individual characteristics and social dynamics affecting vaccine uptake—or lack thereof—remain only partially understood, with most studies having focused on high-income contexts (2–5).

One fundamental factor that shapes health behaviors—including the uptake of vaccines—is individuals' perceptions of general mortality risk (6–8), that is, an individual's subjective assessment of the risk of dying and surviving. Despite being a basic fact of an individual's day-to-day life, with important variations by age, gender, health, socioeconomic, and geographic contexts, individuals' perceptions—and misperceptions—of mortality risk have been systematically documented only in recent years (9, 10). This includes the behavioral and life-course implications of mortality perceptions that deviate from the underlying objective mortality risk that individuals face given their specific context (11–13). In LICs, where overall mortality levels continue to be relatively high and volatile due to epidemics and other crises, pessimistic survival perceptions are common and have received particular attention (6–8).

Such pessimism about survival can be important for behaviors during health crises such as COVID-19 for several reasons: first, pessimistic survival perceptions may lead individuals to underestimate the elevated risk brought about by novel epidemics (e.g., COVID-19), thereby reducing motivation to adopt vaccines and other risk reduction strategies. Second, heightened perceptions of mortality risk diminish the returns to continued investments in health—e.g., via COVID-19 vaccine uptake—where costs are immediate and benefits are incurred only in the future, conditional on survival,

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via reduced infection and disease risks. Third, survival misperceptions may also be a reflection of low levels of health literacy (14–16), such as understanding the importance of healthcare and the benefits of prevention strategies (e.g., vaccination for COVID-19) or biomedical treatments (e.g., antiretroviral treatment (ART) for HIV).

The strength of this paper is the ability to investigate the persistent effects on health-seeking behaviors of a health-information intervention targeting general mortality misperceptions. The specific outcome we study is vaccine uptake during the COVID-19 pandemic, and we argue that these findings may generalize to other critical health behaviors during potential future global health crises. Our analyses leverage a 2017 randomized control trial (RCT) implemented as part of the MLSFH (17, 18) that provided life-table-based information about mortality risks along with narrative information about the determinants of recent mortality trends to evaluate differential vaccination behavior in 2022. While the intervention directly targeted mortality perceptions and the correcting of misperceptions in a population that was heavily affected by the HIV/AIDS epidemic, it also presented respondents with information on the success of health initiatives that have extended life expectancy in the country, which may have indirectly influenced respondents to engage with the healthcare system. Five years after receiving the information, we find that those who received the health-information intervention in 2017 were 7.5 percentage points more likely to be vaccinated compared to the control group in 2022. We also document important indirect effects of the intervention on vaccine uptake by siblings and household members of treated individuals.

While not a new phenomenon, vaccine hesitancy has become a growing public health concern in the United States and around the globe, and the WHO has declared it as one of the top threats to global health (19). Hesitancy was particularly prominent during the COVID-19 pandemic, fueled by misinformation spread over social media platforms and the polarization over vaccine mandates. In addition to the COVID-19 vaccine, there has been opposition in recent years to other vaccines such as Measles, Mumps, Rubella (MMR), Influenza, Human Papillomavirus (HPV), Diphtheria-Pertussis, Tetanus (DPT), and Polio. However, this phenomenon has been primarily studied in the US and other high-income contexts (19–21). Vaccine hesitancy in Sub-Saharan Africa likely differs greatly in scope and determinants, such as inequality of access and the different channels through which vaccine information and misinformation spread through social networks (22).

There is a large literature examining the effects of targeted messaging, reminders, nudges, and financial incentives on increased vaccination uptake for a variety of diseases and vaccines. Generally, these interventions target key motivations for hesitancy including accessibility, trust, and misinformation. Evidence on the impact of these targeted vaccination programs, however, is mixed, with results depending on context and strategy (20, 23–38).

This paper analyzes an intervention that is distinct from most programs aimed at increasing vaccination rates. In particular, the intervention we study took place 5 y prior to the pandemic and thus did not directly target COVID-19 vaccination itself, e.g., by correcting misinformation about the virus or providing direct nudges to get vaccinated. Rather, the MLSFH Benefits of Knowledge (BenKnow) intervention targeted general mortality risk perceptions. Ultimately, this intervention changed vaccine uptake during the COVID-19 pandemic. However, since the intervention was not focused on vaccine uptake or information, the effect sizes we find are difficult to compare to existing studies that explicitly targeted vaccine uptake as part of the intervention.

The large and sustained treatment effects we document on health-seeking behaviors are operating through a variety of direct and indirect mechanisms, and the long-standing relationships with the MLSFH respondents may explain in part why the intervention was successful in significantly changing behaviors. While the messaging of the intervention was straightforward, our trained interviewers spent time with respondents conveying the information in their homes, and the intervention integrated a combination of methods (video narratives, data, and verbal explanation), which likely increased the salience of the messaging among the MLSFH sample. This suggests that external validity may hinge on developing rapport with respondents and committing the time and resources to presenting the information effectively to the target audience.

Context: Rural Malawi and COVID-19

Malawi is among the least-developed countries in the world (39), and it is one of the Sub-Saharan African (SSA) countries that were significantly affected by the HIV epidemic. Adult HIV prevalence peaked at 15.5% in 1998 with 63,000 annual deaths due to HIV/AIDS and is currently at 7.7% with much-reduced HIV mortality due to the expansion of and access to ART (40). The severity of the COVID-19 pandemic for Malawi is less clear. Like other SSA countries, the official COVID-19 infection and death counts are relatively low: based on government reports, cumulatively only 4.5% of the population was infected, and less than 0.2% of the population died of COVID-19 (41, 42). However, seroprevalence tests and analyses of excess mortality indicate that the actual infections were much higher (43, 44).

Malawi participated in the COVAX initiative, a global effort led by GAVI (the Vaccine Alliance), the World Health Organization (WHO), and other partners to ensure equitable access to COVID-19 vaccines for low- and middle-income countries. Malawi initially received shipments of both the AstraZeneca and the Johnson & Johnson vaccines, introducing the Pfizer vaccine in 2022. In the initial phases of vaccination, the government prioritized healthcare workers, the elderly, and other high-risk groups. By the end of 2021, the vaccine was available for everyone in the population, and the government has implemented several programs for increased COVID-19 vaccination uptake including "COVID-19 Vaccine Express" and "Vaccinate my Village" campaigns (45, 46), which increased vaccine access in hard-to-reach communities via the use of mobile vaccination vans. The national vaccination rate (receiving at least one dose) is 26.3% for the total population as of July 2023, while the vaccination rate for the MLSFH sample used in this analysis, which focuses on older Malawians, is 46%.

A distinctive aspect of Malawi and other SSA countries is that the COVID-19 pandemic was preceded by the HIV epidemic that caused substantial fluctuations in mortality. Initially, AIDS-related mortality reduced survival dramatically, especially at adult ages. This trend was only reversed once ART became widely available (47, 48). This "roller coaster" of mortality during the HIV epidemic is likely a factor for why MLSFH respondents have distorted and pessimistic survival expectations. Yet, it is unlikely to be the sole reason: similarly, pessimistic survival perceptions have also been documented in India, Nepal, and the United States (7, 8, 49, 50). MLSFH respondents in 2017 reported an average 5-y survival probability for healthy individuals of 70.3%, compared to the average life table survival rate of 84.6% (Fig. 1*A*).

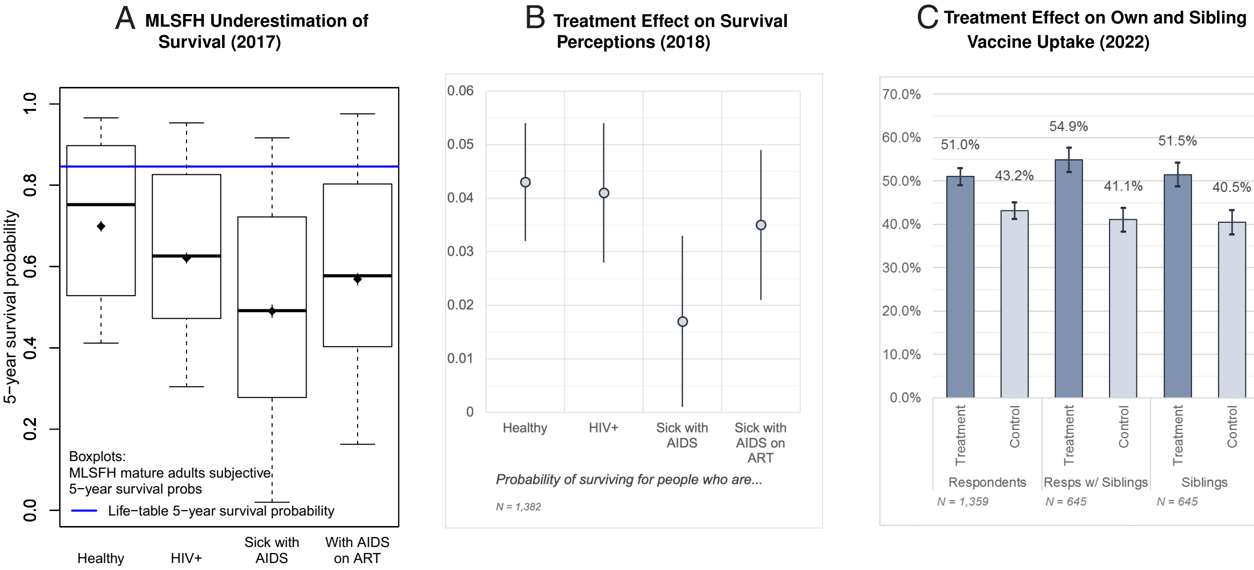

Fig. 1. (*A*) Subjective survival expectations, conditional on health status, reported by Malawi Longitudinal Study of Family and Health (MLSFH) mature adults (aged 45+) who participated in the 2017 Intervention. While respondents correctly assess survival gradients among individuals infected with HIV, sick with AIDS, and on ART, compared to the average life-table 5-y survival probability of 84.6% for this study population MLSFH respondents underestimate survival probabilities even for healthy individuals. (*B*) Impact of the 2017 intervention on 5-y population survival probabilities for individuals who are healthy, HIV+, sick with AIDS, and sick with AIDS and on ART measured 1 y after the intervention in 2018. Except for individuals sick with AIDS, the intervention significantly increased subjective survival probabilities. Estimates are also presented in *SI Appendix*, Table S3. (*C*) 2022 COVID-19 vaccine uptake in the 2017 treatment and control groups (left columns), in the treatment and control groups who have subsequently had their siblings enrolled (middle columns), and among siblings of individuals in 2017 treatment and control groups (right columns). *Notes:* (*A*) Expectations are measured prior to the intervention in 2017. See Materials and Methods Section for additional details on the estimation of the subjective mortality distribution summarized by the boxplots.

Even lower perceived survival rates are reported for those infected with HIV or sick with AIDS. Fig. 1*A* also shows that MLSFH respondents are able to correctly identify the differences in mortality risk for hypothetical persons with differing health statuses (e.g., a healthy person is more likely to survive than a person with HIV or AIDS), alleviating concerns that they misunderstand the survey question about mortality perceptions altogether (for additional analyses of MLSFH mortality perceptions, see refs. 6, 12, and 51–54). *SI Appendix*, Fig. S1 shows that MLSFH respondents are also overly pessimistic in terms of their own survival. While there have been some fluctuations in the extent of MLSFH respondents' survival pessimism during 2006–22, the basic insight has remained unchanged for more than a decade: the vast majority of the adults participating in the MLSFH study underestimate their own and population-level survival.

Elevated mortality expectations and pessimism about survival rates in the MLSFH study population over the last two decades are likely driven by a high frequency of socioeconomic shocks, salient health risks (e.g., HIV/AIDS or other health risks contributing to relatively high adult mortality rates), a lack of accurate health information and limited access to healthcare. In addition, common cognitive biases such as denominator neglect (i.e., tendency to focus on the number of events such as deaths rather than the total people at risk) (55) and salience biases (i.e., tendency to prioritize events that are more memorable or easily recalled over those that are less salient) can lead to an overestimation of mortality risk.

Longitudinal MLSFH Data 2017–22

The Malawi Longitudinal Study of Families and Health is a longstanding longitudinal cohort study started in 1998 to study fertility and social networks and has since expanded to cover many social and contextual determinants of health across the lifecourse. The MLSFH respondents predominantly live in three districts in Malawi (northern, central, and southern regions), with many migrants having been followed outside of these study areas. Almost all of the respondents live in rural areas, where the closest healthcare facility is on average 3.65 km away and only 50% of households own a bicycle, 5% own a motorcycle, and very few own a car. Access to healthcare is therefore limited as it could take, on average, close to 40 min to walk to the closest health center (though we note that during the COVID-19 pandemic many Malawians were vaccinated via mobile vans that traveled to the villages). In 2012, after six rounds of data collection, the Mature Adults Cohort (MAC) was established, targeting MLSFH respondents aged 45 and older to study health and cognition at older ages, and the most recent 2022 data collection effort was the fifth round of the MLSFH MAC. Additional details about our data are provided in *Material and Methods* and *SI Appendix*, sections S3 and S4, as well as the full MLSFH MAC Cohort Profiles (18).

Our analyses use three rounds of MLSFH MAC data: 1) A 2017 survey collecting detailed health and socioeconomic data for the BenKnow study population prior to the implementation of the health information intervention. The survey collected detailed data on both population- and individual-level mortality expectations. (2) A 2018 BenKnow follow-up survey collected relevant follow-up data approximately 12 mo after the health information intervention including information on mortality expectations, health, and other lifecycle behaviors such as savings. (3) A 2022 MLSFH follow-up survey of the ongoing MLSFH MAC, which includes the 2017 BenKnow study population. In addition to these full-length surveys, we also have limited data from a 2021 MLSFH sibling enrollment survey that enrolled approximately 1,000 maternal siblings of MLSFH respondents in the study (56).

While all of the main surveys collect detailed health and socioeconomic data, a main outcome of interest for the 2017 survey and 2018 follow-up was individual and population mortality expectations, elicited using an interactive approach that has been extensively used in the MLSFH and other studies. Respondents were asked to allocate up to 10 peanuts to express the likelihood of an event occurring, allowing respondents to split a peanut in half when stating their expectations (7, 8, 57, 58). Individual mortality expectations measured the perceived likelihood that he/she specifically would die in the next 5 y. The population mortality expectations measured respondents' perceived likelihood that the following hypothetical individuals of a specified health status would die within 5-y period: i) a woman/man who is healthy and does not have HIV; ii) a woman/man who is infected with HIV; iii) a woman/man who is sick with AIDS; iv) a woman/man who is sick with AIDS and is treated with ART. All hypothetical individuals were described as being of the same age and gender and living in the same context as the respondent, and Fig. 1*A* shows the distribution of responses at baseline in 2017.

The 2022 data collection targeted mature adult MLSFH participants aged 45 and above and asked questions about a variety of topics including their health, economic condition, and COVID-19. In addition, the new cohort of siblings of respondents who were enrolled in the MLSFH as part of a 2021 sibling enrollment project were also interviewed. While not a direct follow-up of the 2017 BenKnow health information intervention, a total of 1,302 2017 participants were surveyed in 2022 (652 treatment and 650 control), representing 83.5% of all 2017 participants and 93% of surviving 2017 participants. The 2022 survey also included 581 siblings of participants (293 siblings for the treatment, and 288 for the control group). The analytical sample used in this paper includes respondents who were treated or in the control group in 2017 and were followed up within 2022, and summary statistics are reported in *SI Appendix*, Table S1.

Benefits of Knowledge (BenKnow) Health Information Intervention 2017–18

The 2017 MLSFH BenKnow intervention focused on respondents aged 45 y and older. The BenKnow intervention randomly assigned MLSFH respondents to a treatment or a control group, with randomization occurring at the village level to avoid spillover effects between respondents living in close proximity to one another. Within each of the three MLSFH study districts (Balaka, Mchinji, Rumphi), villages were paired by size starting from the two biggest villages, followed by the two second biggest, etc. Within each pair, one village was randomly assigned to the BenKnow treatment group. As village sizes in the MLSFH study areas vary substantially, this procedure guaranteed a similar sample size and village sizes in the treatment and control group. A total of 118 villages (59 in each treatment and control) were included in the cluster randomization, and the ultimate target sample included 779 respondents in 58 villages for the treatment group and 774 respondents in 57 villages for the control group. The response rate for the BenKnow intervention was more than 98% among 2017 MLSFH survey respondents, resulting in 770 respondents enrolled in the treatment group. A test for balance in baseline characteristics between BenKnow treatment and control groups is reported in *SI Appendix*, Table S2, and more information about the RCT and sample can be found in *SI Appendix*, section S4 and Fig. S4.

The BenKnow intervention was implemented at the individual level and consisted of the following three core components, with the complete interviewer scripts and additional information provided in *SI Appendix*. 1) Narratives about changing mortality patterns in Malawi provided by video clips: Respondents were initially shown three video clips (duration ≈4 min each) in which protagonists (trained local actors following a prepared script) explained how they noticed that people nowadays live longer in rural Malawi. The videos emphasized overall that people live longer due to better access to food, health care, and availability of ARTs for HIV. 2) Life-table survival probabilities conveyed via visual aids: Respondents were shown a health-information sheet with visual information on 5-y and 10-y life-table survival probabilities for individuals of the same gender and within the same 5-y age group. The figures conveyed how many persons, out of 10 alive at the time of the intervention, could be expected to be alive 5 or 10 y in the future. A BenKnow health-information sheet is illustrated in Fig. 2, with full version included in *SI Appendix*. The script accompanying these sheets purposely emphasized both the survival and mortality risk to avoid anchoring. 3) Postintervention follow-up questions: Respondents were asked a set of interactive questions immediately following the presentation of video narratives and life-table information that probed comprehension of the BenKnow information and re-elicited mortality perceptions, with additional follow-up if a respondent didn't change responses from the preintervention questions. Almost all (98%) of the respondents reported understanding the provided survival/mortality risk information, and 79% state that the information reflected correctly what had been happening in their community, with 15% stating that it reflected it somewhat correctly. Overall, interviewers spent approximately 20 to 25 min with each respondent showing them the videos, explaining the life-table sheets and asking them about their mortality perceptions after receiving the intervention information. In addition to the time spent with the MLSFH respondents in their homes, we note that there is a longstanding relationship with the respondents, cultivated over many survey waves. On average, participants completed 8.7 out of 12 total prior MLSFH surveys, and over 95% of the sample participated in at least five surveys, which may have made the intervention more salient to the MLSFH respondents.

Focusing on sexual behaviors during the period 2017–18, an initial analysis of BenKnow impacts (51) found that receiving information about population mortality risk and viewing the video narratives increased subjective population survival perceptions and reduced sexual risk taking. Specifically, there was a

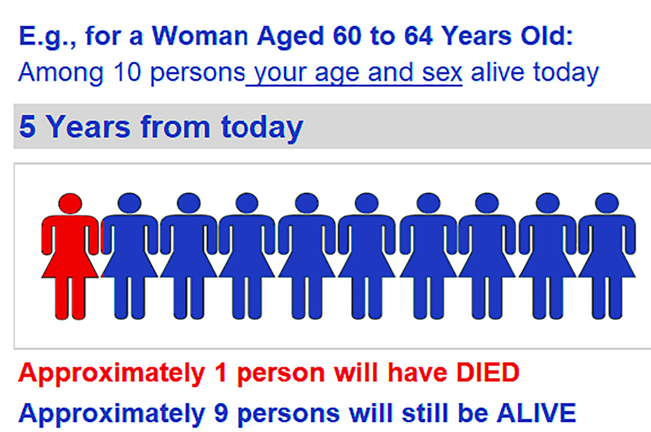

Fig. 2. BenKnow intervention: life table information presented to participants. *Notes:* The 2017 BenKnow health information intervention provided life-table-based information about age- and genderspecific 5-year and 10-year mortality risks and survival probabilities to 770 individuals aged 45+ in rural Malawi, with 774 individuals serving as controls.

Table 1. Impact of BenKnow on 2022 vaccination status—linear probability models

	(1)	(2)
Treatment effect	0.075**	0.076**
	(0.036)	(0.036)
Covariates included	N	Y
Control mean	0.43	0.43
Observations	1,359	1,359
Number of clusters	114	114
R-squared	0.151	0.160

Notes: Estimates from linear probability models with fixed effects for randomization strata. Robust SE in parentheses, clustered at the village level. The outcome is measured as a dichotomous variable indicating whether or not the respondent reported having received at least one dose of the COVID-19 vaccine as of the 2022 survey. In the cases where the respondent was interviewed in 2021 but not in 2022, the reported 2021 vaccination status is used. Column (1) shows the treatment effect on vaccination status without any demographic covariates included. Column (2) adds gender, age, and education to the regression (see *SI Appendix*, Table S4 for more detail). A time dummy for being surveyed in 2022 is also included in all analyses. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

positive treatment effect on subjective probability of survival among hypothetical healthy individuals, HIV+ individuals, and people with AIDS on ART (replicated in Fig. 1*B* and *SI Appendix*, Table S3). They do not find, however, any effect on own subjective probability of survival, most likely because people have private information about their own health, which makes this perception less responsive to new information. These analyses additionally document a 19% reduction (or 1.2 percentage point reduction) in the predicted probability of risky sex (defined as having multiple partners without a condom), an 8% increase in the predicted probability of abstinence for the treatment group compared to the control group 1 y after the intervention, and a 1.6 percentage point increase in the probability of being married.

We extend these initial BenKnow analyses by analyzing the longer-term impacts of the intervention, focusing in particular on vaccine uptake during the COVID-19 pandemic and possible pathways through which the intervention may have affected health-seeking behaviors 5 y after its implementation [e.g., health care seeking, life-cycle behaviors, and perceptions of biomedical treatments, none of which were included in prior analyses (51)].

Lasting Effects of the BenKnow Health Information Intervention on COVID-19 Vaccination Behavior

Treatment Effects on COVID-19 Vaccine Uptake. Our key findings pertain to the effect of the BenKnow health information intervention on COVID-19 vaccine uptake about 5 y after the intervention (Table 1 and Fig. 3). We find that assignment to the treatment group in 2017 significantly increases the likelihood of being vaccinated against COVID-19 in 2022. Overall, as of the 2022 survey, 51% of the treatment group is vaccinated compared to 43% of the control group (Fig. 1*C*). Results from linear probability models indicate that being in the 2017 treatment group results in a 7.5 percentage point increase (or 17.4% of the control mean) in the probability of being vaccinated (receiving at least one dose of the COVID-19 vaccine) in 2022 compared to individuals in the control villages ($P = 0.041$). These treatment effects are detectable in 2022 (Table 1), when average vaccine uptake was around 46% in our study population, and were smaller in magnitude and not statistically significant in 2021 (Fig. 3 and *SI Appendix*, Table S5) when uptake was only 23%. Hence, relatively easy access to COVID-19 vaccines, which was

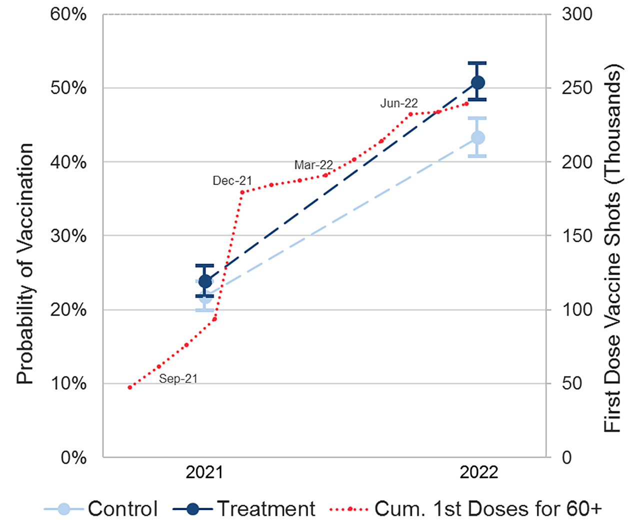

Fig. 3. Predicted probabilities of vaccination by BenKnow treatment status. *Notes:* Predicted probabilities from linear probability models in Column (1) of Table 1 (for 2022) and *SI Appendix*, Table S5 (for 2021). 2021 vaccination status collected in November and December 2021; 2022 vaccination status collected between August and October 2022. Cumulative first doses of COVID-19 vaccines (red dotted line) measured monthly using data from the Malawi Ministry of Health from August 2021 to August 2022 for people aged 60 years and older.

the case in mid-2022 in rural Malawi, was key for the BenKnow intervention to significantly affect vaccine uptake.

Social Multiplier Effects: Siblings and Household COVID-19 Vaccination. We also find evidence that the information from the intervention spread through family networks (Table 2):

Table 2. Family network spread of vaccination behavior

	Siblings		Household	
	R Vacc (1)	S Vacc (2)	% Vacc (3)	# Vacc (4)
Treatment effect	0.143***		0.062**	0.253***
	(0.045)		(0.024)	(0.089)
Sibling in treatment group		0.128***		
		(0.041)		
Control mean	0.397	0.405	0.307	1.08
Observations	575	575	1,302	1,302
Number of clusters	109	104	114	114
R-squared	0.256	0.240	0.146	0.175

Notes: Estimates from ordinary least squares (OLS) regressions, including fixed effects for randomization strata in all regressions. Robust SE in parentheses, clustered at the village level. Vaccination status is measured as a dichotomous variable indicating whether or not the respondent/sibling reported having received at least one dose of the COVID-19 vaccine as of the 2022 survey. Column (1) shows the treatment effect on vaccination status of the respondent (for the subsample of respondents that have an enrolled sibling) while Column (2) shows the effect of the original respondent's treatment status on their sibling's vaccination status. For household vaccination, respondents were asked how many people lived in the household, and how many members of the household received at least one dose of the COVID-19 vaccine. Columns (3) and (4) show the treatment effects on the reported percentage and number of household members that are vaccinated, respectively. All regressions control for gender, education, and age. For Columns (1) and (2), when 2022 vaccination status is not available, 2021 vaccination status is used and a time dummy for being surveyed in 2022 is included. This is not possible for the household regressions as household vaccination rates were only asked in 2022. The randomization strata fixed effects and SE clustering in Column (2) refer to the original BenKnow respondent's village and strata. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

siblings of treated respondents are significantly more likely to be vaccinated than siblings of respondents in the control group. While this can only be analyzed for a subset of respondents whose biological siblings were enrolled in 2021 and followed up in 2022, siblings of the treated individuals are 12.1 percentage points ($P = 0.003$) more likely to be vaccinated than siblings of the control group. The direct treatment effect on respondents' vaccination behavior within the subsample of respondents with enrolled siblings is also higher than the overall treatment effect (14.3 percentage points compared to 7.5 percentage points for the whole sample). The higher treatment effect may be related to the structure of the sibling enrollment process (which prioritized proximity, closeness in age, and same gender for siblings and was limited on time for in-person enrollment), resulting in demographic differences between groups. The treatment group in the subsample of respondents with siblings is slightly younger (<2 y on average) and more educated (similar to the full sample), and we control for these differences in all regressions. (See *SI Appendix*, Table S6 for specific information on demographic differences between groups.) We also find that treated individuals have more overall household members and a larger fraction of their household vaccinated (Table 2), further supporting the finding that the intervention effects spread within the family networks of treated individuals. Being in the treatment group is associated with a 6.2 percentage point increase in household vaccination and 0.25 more people being vaccinated in the household.

Robustness, Heterogeneity, and Attrition. A common concern for any study of self-reported vaccination status is the possible misreporting and desirability bias in the survey. The study team weighed the trade-offs between requiring a vaccination card to be shown in order to verify vaccination status with the additional time this would require in an already long survey, plus the likelihood that many respondents did not have or could not find their vaccine cards (in addition to being a low-income rural environment, there were also no vaccine mandates in Malawi requiring proof of vaccination). We ultimately decided that requiring vaccination cards would be too burdensome, and would also introduce measurement error (e.g., respondents who can't find their vaccine cards, for some reason didn't receive one, or were interviewed outside of their usual residence where the vaccine card is stored). Instead of insisting on vaccine cards, we opted for asking the timing and brands of vaccine to assess the plausibility of the self-reported vaccination status. Self-reporting bias would be problematic for our estimate of the treatment effect if it varied across treatment and control groups. However, this is unlikely to be the case since the BenKnow intervention occurred 3 y prior to the COVID-19 pandemic and did not mention any vaccine specifically. We also compare the self-reports to national vaccine trends in Malawi (*SI Appendix*, Fig. S3), and test the robustness of the results, excluding individuals with inconsistent or incomplete vaccination data (see *SI Appendix*, Table S10 and note this potential misreporting is balanced across treatment and control groups), all of which consistently support and verify our primary findings. Our key finding about the BenKnow impact on 2022 vaccine uptake is also robust to adjusting for multiple hypothesis testing in joint analyses of all 2022 outcomes for the main sample (including the pathways elaborated below) (*SI Appendix*, Table S11). More detail on this and other robustness tests can be found in *SI Appendix*, section S2.

SI Appendix, section S2 also contains analyses of heterogeneous treatment effects and attrition analyses. Acknowledging that the BenKnow intervention was powered to estimate the main treatment effects only, we do not detect any statistically significant heterogeneity of treatment across certain demographic and health-related factors including gender, age, or the presence of comorbidities for COVID-19. Nor do we detect any differences in the treatment effect by baseline misperception of survival risk. However, we do find a positive and significant treatment effect when treatment is interacted with a dummy variable for having no formal schooling, suggesting that the intervention was most effective for those without formal education (Column 2 of *SI Appendix*, Table S13).

Finally, we observed an attrition rate of approximately 16 percent between 2017 and 2022, primarily attributable to individuals who had passed away, which might be expected in an older cohort facing fairly high mortality levels. Importantly, our attrition analysis reveals no differential attrition between the treatment and control groups, nor any discernible attrition patterns by vaccination status.

Pathways and Correlates of Vaccine Uptake

A major advantage of the MLSFH is the richness of the data, which allows us to not only document the effects of the BenKnow intervention on our key outcome—COVID-19 vaccination uptake—but also gain insights into the possible mechanisms through which the health information intervention affected individuals' behaviors. Fig. 4 illustrates the pathways through which the BenKnow intervention potentially influences COVID-19 vaccination. Foremost, the intervention directly targeted pessimistic survival perceptions, and being a key component of any health decision-making, any resulting increases in expectations of survival can affect COVID-19 behaviors. Several other pathways are possible as well and are not mutually exclusive from perceptions about survival. In addition to giving respondents information about the probability of survival, the BenKnow intervention highlighted the fact that people lived longer in Malawi due to the availability of ART and other successful health initiatives in the country. It is therefore plausible that the respondents believed the health care system and biomedical treatments were key to the mortality improvements in Malawi, and the treatment effect on vaccination is operating through increased healthcare-seeking behavior motivated by higher trust and belief in modern medicine. In making these connections, the intervention closes health literacy gaps that may prevent individuals from seeking care in the formal sector or trusting public health guidance when a novel epidemic arises. As a final potential pathway, we also posit that any lasting effects of the BenKnow interventions on savings, investments, and other forward-looking behavior can affect COVID-19 behaviors by affecting participants' economic resources. Finally, an improvement in health behavior can have a reinforcing effect on survival perceptions, and thus on all other behaviors. In the subsequent sections, we provide evidence that three out of these four possible pathways in Fig. 4 contributed to BenKnow impacts of vaccine update.

Pathway 1: Effects on survival perceptions. One year after implementation, participants receiving the BenKnow health information intervention expressed improved population survival probabilities [Fig. 1*B* and (51), with regression analyses reported in *SI Appendix*, Table S3, Columns (1)–(4)]: survival probabilities increased by 4 to 5 percentage points for hypothetical healthy and HIV+ persons and also increased by 3.5 percentage points for persons sick with AIDS and on ART, whereas they increase by only 1.7 percentage points for persons sick with AIDS (and

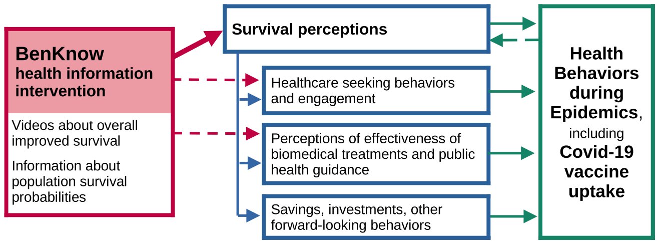

Fig. 4. BenKnow intervention: potential pathways affecting COVID-19 behaviors.

not on ART). Importantly, the differential treatment effect for persons sick with AIDS depending on whether the person is on ART indicates that participants attributed the improved survival rates to the increased availability of ART which was introduced in the MLSFH study regions around 2008 and emphasized in the video clips shown to respondents during the intervention. Unfortunately, the lack of population survival perceptions in the 2022 MLSFH follow-up prevents us from investigating whether treatment effects on population survival perceptions persisted until 2022. It should be noted, however, that while there is a positive treatment effect on population survival perception in 2018, we find no effect of the treatment on individual survival perceptions in 2018 or 2022, suggesting that the change in health behavior is due to a change in population survival perceptions, and individual survival perceptions are more difficult to change given the private information people have about their own health risks [*SI Appendix*, Table S3, Columns (5) and (6)].

Pathway 2: Health-seeking behavior. The BenKnow intervention had a sustained effect on health care utilization that started to emerge in 2018 (1 y after the intervention) and became more pronounced during the COVID-19 pandemic at the 2022 follow-up. Specifically, treated individuals increased their likelihood of going to hospitals and clinics when seeking medical treatment or care, and decreased their likelihood of using traditional healers or traditional medicine (Table 3). While there is no difference at baseline in the exclusive use of hospital and clinics (respondent doesn't use traditional healers) (Column 1), there is a treatment effect of 2.2 percentage points in 2018 and 3.2 percentage points in 2022 (the latter being statistically significant at the 5% level). Additionally, treated individuals were 3.8 percentage points less likely to use traditional healers in 2022 ($P = 0.01$). Using 2022 data on heath care utilization (e.g., the number of times a respondent visited specified healthcare facility types such as pharmacy, public hospital, private health clinic, traditional healer, etc.), we find that use of public hospitals significantly increased in 2018 and 2022 for the treatment group, while use of traditional healers significantly decreased in the follow-up years (*SI Appendix*, Table S7).

The results are robust to controlling for vaccination status, thus ruling out the possibility of hospital visits for the purpose of receiving the vaccine. This interpretation is supported by the fact that only 2.4% of respondents stated that the most recent reason for needing healthcare was COVID-19 vaccination, and the observation that unvaccinated individuals who received the BenKnow intervention are less likely to report lack of trust as a reason for not being vaccinated (with lack of trust capturing distrust in government/healthcare workers, distrust in vaccine efficacy, or trust in traditional healers; see *SI Appendix*, Fig. S2).

Pathway 3: Perception of biomedical treatment. Utilizing 2022 data on expectations about COVID-19 infection and mortality risks, Table 4 shows that respondents in the treatment group were less likely in 2022 to believe they would be infected with COVID-19 or die if they were infected. Because of a heaping of survey responses on values such as zero (no chance) and five (equal chance), our analyses in Table 4 use two specifications: first, an ordered logit with fixed effects [Column (1)] where the outcome is a 5-point scale of likelihood (very low, low, equal chance, high, very high), showing that treated respondents are less likely to believe they will be infected with COVID-19. The overall average marginal effect is -0.203 ($P = 0.078$) which translates into a 4.8 percentage point higher average marginal likelihood of answering that there is a very low expectation of infection. While ordered logit results for expectations of death if infected are statistically insignificant, the relationship is negative. Second, we use linear probability models where the outcome is measured as "high" and "low" likelihood for greater than and less than

Table 3. Impact of treatment on likelihood of using hospitals, clinics, and traditional healers—linear probability models

	2017 Baseline		2018 Follow Up		2022 Follow Up	
	HC (1)	TH (2)	HC (3)	TH (4)	HC (5)	TH (6)
Treatment	0.009 (0.016)	−0.002 (0.015)	0.022 (0.016)	−0.014 (0.015)	0.032** (0.015)	−0.038*** (0.014)
2017 Use of HC			0.247*** (0.032)		0.148*** (0.030)	
2017 Use of TH				0.247*** (0.034)		0.158*** (0.033)
Control mean	0.151	0.837	0.147	0.837	0.162	0.837
Observations	1,541	1,541	1,480	1,480	1,302	1,302
Number of clusters	115	115	115	115	114	114
R-squared	0.067	0.071	0.124	0.124	0.087	0.085

Notes: Outcome variable corresponds to where the respondent is most likely to go when they need medical treatment or care. Possible answers are i) hospitals/clinics; ii) traditional healers/traditional medicine, iii) both equally, or iv) don't use either. HC stands for hospitals and clinics, TH stands for traditional healers. Use of hospitals and clinics includes respondents that *only* use hospitals and clinics, while use of traditional healers includes respondents who only use traditional healers as well as those that use both hospitals/clinics and traditional healers equally. "Neither" is included in the base category of both HC and TH. Estimates from linear probability models with fixed effects for randomization strata. Robust SE in parentheses, clustered at the village level. All regressions control for age, gender, and education. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

Table 4. Impact of treatment on COVID-19 subjective expectations

	Ordered Logit (1-5) (1)	High Likelihood (>50) (2)	Low Likelihood (<50) (3)
Infection with COVID-19:			
Treatment	−0.203*	−0.011	0.046**
	(0.115)	(0.011)	(0.018)
Control mean	1.76	0.08	0.75
Observations	1,295	1,298	1,298
Number of clusters	111	114	114
R-squared	0.009	0.037	0.066
Death if infected with COVID-19:			
Treatment	−0.093	−0.044*	0.001
	(0.116)	(0.023)	(0.024)
Control mean	2.28	0.13	0.53
Observations	1,293	1,296	1,296
Number of clusters	111	114	114
R-squared	0.006	0.069	0.054

Notes: Subjective Expectations elicited using a choice out of 10 peanuts to represent the probability of infection/dying if infected. Column (1) shows the average marginal treatment effects of ordered logit regressions on a 1 to 5 scale. The scale represents the subjective expectation of infection/dying if infected, where 1 = 0 to 24%, 2 = 25 to 49%, 3 = 50%, 4 = 51 to 75%, 5 = 76 to 100%. Columns (2) and (3) show estimates from linear probability models, where high likelihood is greater than 50% and low likelihood is less than 50% subjective expectation of infection/dying if infected with COVID-19. Robust SE in parentheses, clustered at the village level. All regressions control for age, gender, and education. Fixed effects for randomization strata are also included. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

50% (5 out of 10 peanuts), respectively. These results show that treated respondents are 4.6 percentage points ($P = 0.013$) more likely to believe there is a lower than 50% chance of infection and 4.4 percentage points ($P = 0.063$) less likely to believe there is a greater than 50% chance of death if infected with COVID-19 compared to the control group.

As the vaccine significantly prevents likelihood of COVID-19 infection and death if infected, and the treatment group is more likely to be vaccinated, these treatment effects may be interpreted as the respondents' belief in the effectiveness of the vaccine. To further support this argument, we also analyze survival expectations for other diseases with available treatment, elicited in the 2018 survey. We asked respondents the survival probabilities of hypothetical individuals with hypertension, diabetes, and AIDS with and without the appropriate medication. The difference in the survival probabilities with and without medication measure the respondent's perceived returns to the medication in terms of survival. We present in Table 5 the BenKnow treatment effect on these perceived returns. We see a positive and precisely estimated treatment effect for hypertension and diabetes, representing two relatively newly emphasized noncommunicable diseases in the MLSFH study areas. The coefficient for AIDS is also positive but less precisely estimated. Note that there is a positive treatment effect on the survival probabilities of AIDS patients on ART in Fig. 1*B*, but not on the returns as defined in Table 5. These results are consistent with the change in population survival perceptions as the intervention attributed much of the increase in survival to health initiatives such as the availability of ART.

Pathway 4: Effect on forward-looking behaviors. We also explore the possibility that certain forward-looking behaviors are a pathway for vaccination decisions. We analyze whether wealth, savings, investment, and animal ownership were impacted by the intervention, such that treated individuals expect to live longer and decide to invest in their future. While there is some evidence of increased investment in agricultural tools and animals (particularly chicken) in 2018, the results do no persist into 2022, and we can therefore not confidently conclude that these pathways had a meaningful impact on vaccination behavior (see *SI Appendix*, Table S8 for these results).

Table 5. Treatment effect on 2018 difference in survival expectations—*on medication vs. not on medication*

	Hypertension (1)	Diabetes (2)	AIDS (3)
Treatment effect	0.033***	0.030**	0.026
	(0.010)	(0.014)	(0.018)
Control mean	0.171	0.174	0.184
Observations	1,456	1,456	1,426
Number of clusters	115	115	115
R-squared	0.087	0.116	0.087

Notes: Estimates from OLS regressions with fixed effects for randomization strata. Subjective expectations elicited using a choice out of 10 peanuts to represent the probability of dying, converted into the probability of survival (from 0 to 1). Survival gaps are measured as the difference in 5-y survival expectations for a hypothetical person of the same age and gender being on medication vs. not being on medication for hypertension [Column (1)], diabetes [Column (2)], and AIDS [Column (3)], all measured at the 1 y follow up in 2018. The control group means show that the average difference between subjective survival probability of those on medication vs. off of medication (17 to 18% higher 5-y survival probability if a person is on medication). Robust SE in parentheses, clustered at the village level. All regressions control for age, gender, and education. Column (1) additionally controls for hypertension at baseline, Column (2) additionally controls for diabetic at baseline, Column (3) additionally controls for the baseline HIV status of the respondent. Fixed effects for randomization strata are included. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

Discussion and Conclusion

Our analyses document the long-term impact of the BenKnow health information intervention that was designed to reduce misperceptions of survival risk in a SSA low-income population. Initial analyses, focusing on sexual behaviors during the period 2017–18 (51), have shown that the BenKnow intervention had persistent effects on pessimistic population survival expectations and reduction in sexual risk taking. We expand these findings, and focus on the impacts of BenKnow on health-seeking behaviors during the COVID-19 pandemic, 5 y after the intervention. We thus document long-term effects of the BenKnow intervention, and more importantly, we document the impacts of the RCT on critical health behaviors during a global pandemic that was unforeseen at the time of the intervention.

Our analyses show that, 5 y after implementation of the intervention, participants in the BenKnow treatment group had a 7.5 percentage point higher likelihood of COVID-19 vaccination compared to the control group (Table 1). This treatment effect gradually emerged as vaccines became increasingly available during the pandemic (Fig. 3). Additionally, siblings of the intervention participants are also more likely to be vaccinated, and treated individuals have higher household vaccination rates, indicating that there were indirect effects through family networks (Table 2).

The findings of this study provide valuable insights into the impact of health information interventions on health-seeking behavior and risk reduction strategies, particularly in the context of an unexpected health shock such as the COVID-19 pandemic. While the primary objective of the intervention was to address survival misperceptions, the observed behavioral changes 5 y after the intervention are likely due to both direct and indirect pathways. Likely because the BenKnow video narratives emphasized the success of public health programs, respondents began to engage more with the formal healthcare system. As described in Fig. 4, increased vaccination behavior among the treatment group can be attributed to a mix of higher population survival perceptions, increased engagement with the formal healthcare system, and increased perceptions of the effectiveness of biomedical treatments. While we may not be able to directly measure the contribution of each channel to the treatment effect on vaccination, it is likely a combination of these pathways (which are not mutually exclusive of one another) over the short and medium term that ultimately results in an individual's decision to get vaccinated.

The existing evidence on behavioral interventions that directly target increased uptake of a specific vaccine—e.g., via nudges, reminders, education and overcoming barriers, etc.—is mixed, and focuses primarily on the United States and other Western nations. It is difficult to compare estimates from these studies to our results as our intervention did not directly target increased vaccination rates for COVID-19. Our paper instead documents how a health information intervention aimed at correcting misperceptions about survival influenced other general health behaviors, including vaccination uptake during an unforeseen pandemic.

The BenKnow intervention achieved the primary objective of reducing overly pessimistic beliefs about population survival risk (Fig. 1*B*), and had an indirect benefit of increasing confidence in the effectiveness of biomedical treatments via higher survival perceptions which resulted in changed health behavior. This is especially encouraging since the COVID-19 pandemic could not have been anticipated during the intervention, and suggests these types of interventions can be key to combating unexpected health crises and new diseases without directly promoting a specific treatment or vaccine.

The change in population survival perceptions that we document is consistent with the positive treatment effect on engagement with the formal healthcare system. By focusing on the success of past health initiatives and treatment, the intervention boosted visits to hospitals and clinics, and reduced reliance on traditional healers (who may not be equipped to handle prevention strategies and treatments for epidemics). In particular, the move away from traditional healers and toward hospitals and clinics indicates heightened awareness among BenKnow participants of the success of public health programs to make ART available to HIV-positive Malawians, giving them a greater incentive to use government healthcare facilities. The increased belief about the efficacy of modern medicine suggests that the treatment group may have been more receptive to medical interventions, including vaccinations, as a means to safeguard their health against the uncertainties posed by novel diseases like COVID-19.

We also find that the positive treatment effect on safe sex practices in 2018 reported in prior analyses (51) persist into 2022 (*SI Appendix*, Table S9). These results are consistent with the COVID-19 vaccine results highlighted in the present paper as both safer sex in the context of the HIV epidemic and vaccines during the COVID-19 pandemic present effective risk reduction strategies that were adopted by individuals subsequent to the BenKnow intervention, without the intervention mentioning either one of them directly.

The intervention had large and lasting effects. The generalizability of these sustained results, however, may depend on key aspects of the intervention itself, which was more complex than a simple message presented in a group setting or via email/text message. The sample of Malawians targeted for the intervention were already part of the MLSFH cohort and had been repeatedly interviewed in the prior decade before the intervention. As such, it is likely that BenKnow had large effect sizes due to trust that had been built with the respondents over many years and a willingness of respondents to believe the information that the MLSFH survey interviewers presented to them. Additionally, while the intervention content may seem simple, BenKnow was multilayered, using a combination of integrated videos, graphics, verbal explanation, and follow-up questions, the format and content of which were both novel and engaging to the respondents. This point is further emphasized by the fact that the interviewers individually went to the respondents' homes and sat with them for 20 to 25 min to describe the mortality sheets and present the video narratives. It should also be noted that 2017 was the first year the MLSFH had implemented tablets for data collection. Presenting the BenKnow videos to respondents via tablet was likely novel and noteworthy to the respondents, making the messaging more salient.

We also acknowledge that BenKnow was designed as a "proof of concept" and feasibility study embedded within the MLSFH, with future implementation studies refining the study design and messaging approach after analyses—such as the current one—have established lasting and relevant BenKnow treatment effects. Scale-up of the intervention to other populations will require additional implementation research to refine the study design and procedures. Yet, the emerging evidence on the effectiveness of the BenKnow intervention for improving health behaviors in the short term (51) and in the medium/long-term during the COVID-19 pandemic (this paper) suggests that interventions that are focused on mortality misperceptions—such as BenKnow—deserve further attention and research.

We additionally note limitations that cannot be addressed in our analyses, mostly due to the fact that the 2022 MLSFH survey was not explicitly designed to be a direct follow-up of the BenKnow intervention (BenKnow funding supported only the 2018 1-y follow-up). As a result, some data on perceptions, such as population mortality perceptions, were not asked, nor were perceptions about the COVID-19 vaccine in 2022. We also acknowledge that while the intervention was successful in changing population mortality perceptions in 2018, we see no change in individual-level mortality perceptions in 2018 or 2022. Future research is needed to understand how to reduce pessimism about one's own survival. Additionally, the vaccination data is self-reported by the respondents, but we feel confident in the responses as we asked for additional information regarding vaccination including the date of vaccination and brand of vaccine. Finally, given the size of the sample, the study was not designed and powered to systematically identify heterogeneous treatment effects; nevertheless, we find evidence that the treatment effect was strongest for respondents without formal education.

Despite these limitations, the results of this paper have significant implications for public health strategies, especially in regions where the population has been deeply affected by high disease burdens and prolonged epidemics. The persistence of pessimistic survival expectations in these populations underscores the enduring influence of previous health crises on individuals' perceptions of population mortality risks. By correcting misperceptions and underscoring the benefit of medical treatment, interventions such as BenKnow can foster trust in medical systems and public health guidance which leads to proactive behavior to get treated or vaccinated. We note that this trust is hypothesized as it not explicitly measured and is an area for future research to test. In addition to their relevance for increasing vaccine uptake during the COVID-19 pandemic, our findings are important because they suggest that efforts to reduce mortality misperceptions by providing information about the level and determinants of population-level mortality can be an important component of global health efforts to prepare populations for future epidemics. As low-income countries grapple with unforeseen health crises, the provision of accurate information about survival expectations and public health efforts emerge as a powerful tool to promote essential health behaviors, such as vaccination, and thus mitigate the impact of emergent diseases on public health. Understanding how individuals in SSA LICs perceive mortality and respond to health guidance during epidemics, particularly after enduring the devastating consequences of HIV and then a decade of rapid improvement in life expectancy post-ART availability, is important for population health and vitality.

Materials and Methods

Fig. 1*A* Details. The boxplot-like graph displays the mean (dot) and median (center line) of the corresponding 5-y survival expectations, as well as the 10th (lower whisker), 25th (bottom of the box), 75th (top of the box), and 90th (upper whisker) percentiles of the distribution. Life-table survival probabilities are merged by age and gender from the UN Malawi 2005–15 life tables (UN Population Division 2017).

MLSFH. The MLSFH is a population-based cohort study with 12 rounds of data collection during 1998 to 2022 that provides a rare record of more than two decades of demographic, socioeconomic, and health conditions in one of the world's poorest countries (17, 18). While the MLSFH is not nationally representative, comparisons with the rural samples of the Malawi DHS (59) and IHS (60) confirm that the MLSFH study population continues to match closely the characteristics of nationally representative surveys (17, 18). The initial MLSFH sample was established using a cluster random sampling strategy (Mchinji and Rumphi) and by drawing a subset of an earlier representative population survey (Balaka). In 2008, the MLSFH sample was extended to older ages by enrolling a sample of parents of the original MLSFH respondents to increase the suitability of the MLSFH for studying intergenerational aspects and the health of older individuals. The MLSFH study population has been followed up until 2022 (including migration follow-ups), with 2012–18 data collections focusing on a subset of MLSFH respondents aged 45+ (Mature Adult Cohort), and the 2019 data collection following-up on the remaining MLSFH respondents (including older respondents who previously were not included in 2012–18). In 2022, MLSFH respondents aged 45+ were surveyed again, including about 1,000 maternal siblings who were identified during a 2021 MLSFH sibling enrollment. Cohort profiles (17, 18) as well as *SI Appendix*, section S3 provide detailed information about sampling, study instruments, attrition/follow-up rates, and data quality.

Empirical Specifications and Definitions of Outcomes. Our main results (Table 1) showing the treatment effect on COVID-19 vaccine uptake are estimated using the following linear probability empirical specification:

$$V_{ij} = \beta T_j + X_{ij}\gamma + \tau_s + \delta_{2022} + \epsilon_{ij}, \qquad [1]$$

where V_{ij} is a dichotomous variable indicating whether or not individual i living in village j at the time of the intervention reported having received at least one dose of the COVID-19 vaccine in 2022. In the cases where the respondent was interviewed in 2021 but not in 2022 (n = 57), the reported 2021 vaccination status is used. T_j is an indicator for the respondent living in a village assigned to the treatment group in 2017 and receiving the treatment, X_{ij} is a vector of respondent demographic characteristics including 5-y age bracket, gender, and categorical education status (no formal schooling, primary schooling, secondary or higher schooling). Note that Column (1) of Table 1 does not include the vector of covariates. τ_s represents fixed effects for randomization strata s indicating village pairs, δ_{2022} represents a survey round dummy for the respondent being interviewed in 2022, and ϵ_{ij} represents the idiosyncratic error term. SE are clustered at the village level and are robust to account for any heteroscedasticity. We also considered using probit models or conditional logit models in place of linear probability models (LPM). Probit models, while producing similar results to the LPM estimates, have an incidental parameters problem when using high dimensional fixed effects for randomization strata. Conditional logit models with fixed effects do not allow for fixed effects that are not nested within the clusters so we cannot have a specification with randomization strata fixed effects and clustering at the village level. Additionally, while the LPM remains consistent in the presence of heteroskedacity, the fixed-effects conditional logit estimator does not have the same robustness properties. We therefore use linear probability models with fixed effects for randomization strata for our main results. We use a similar empirical specification for the analysis of family network vaccination (Table 2), where linear probability models are used to estimate the effect of treatment on respondents' vaccine uptake for the subsample of respondents that have siblings, as well as the impact on vaccine behavior for sibling-respondents who have a sibling that was part of the intervention [Columns (1) and (2) of Table 2, respectively]. The sibling treatment effect [Columns (2) of Table 2] is estimated using the following specification:

$$V_{kj} = \beta T_j + X_{kj}\gamma + \tau_s + \delta_{2022} + \epsilon_{kj} \qquad [2]$$

where V_{kj} is a dichotomous variable indicating whether or not individual k, who is a sibling of a 2017 BenKnow respondent who lived in village j at the time of the intervention, reported having received at least one dose of the COVID-19 vaccine in 2022. In the cases where the sibling-respondent was interviewed in 2021 but not in 2022 (n = 67), the reported 2021 vaccination status is used. T_j is an indicator for respondent k's sibling living in village j assigned to the treatment group in 2017 and receiving the treatment, X_{kj} includes the same demographic characteristics as [**1**], τ_s represents fixed effects for the BenKnow sibling's randomization strata s, δ_{2022} represents a survey round dummy for respondent k being interviewed in 2022, and ϵ_{kj} represents the idiosyncratic error term. OLS models with fixed effects for randomization strata were used to estimate the impact of treatment on the respondent's household vaccination, where V_{ij} in Eq. **1** is replaced with the percentage of the household and number of household members vaccinated as outcomes [Columns (3) and (4) of Table 2, respectively]. Table 3 estimates Eq. **1** using healthcare utilization as the outcome. Specifically, the outcomes indicate the type of healthcare the respondent is most likely to seek when they need medical treatment or care: hospitals/clinics, traditional healers/traditional medicine, both equally, or don't use either. We create dummies for HC (use of hospitals and clinics exclusive of traditional healers), and TH (use of traditional healers either exclusively or equally with hospitals and clinics), so the regression estimates show similar results from different perspectives (the only difference being that neither is included in the base category of both HC and TH). Subjective Expectations from Table 4 were elicited using a choice out of 10 peanuts to represent the probability of infection with COVID-19 or dying if infected from COVID-19. These expectations were converted into three outcome variables: 1) a scale from one to five, where 1 = 0 to 24%, 2 = 25 to 49%, 3 = 50%, 4 = 51 to 75%, 5 = 76 to 100%; 2) a dichotomous indicator for high likelihood (greater than 50%) of infection/dying if infected with COVID-19; and 3) a dichotomous indicator for low likelihood (less than 50%) of infection/dying if infected with COVID-19. Column (1) of Table 1 is estimated using an ordinal logistic regression with fixed effects, and estimates show the marginal effect at the sample average. Columns (2) and (3) of Table 4 again estimate Eq. **1** using subjective expectations as the outcome. Finally, Table 5 shows OLS estimates of the treatment effect on perception of biomedical treatments (measured in 2018 as part of the 1-y follow-up), including the same covariates and fixed effects as Eq. **1**. Because we are analyzing the treatment effect on multiple outcomes and pathways, we perform multiple hypothesis tests (MHT) for all main results using the full sample in 2022. We use the sharpened false discovery rate (FDR) Q-values introduced by Michael Anderson (61) and show that all of the main results from Tables 2–4 hold in *SI Appendix*, Table S11. We additionally use sharpened Q-values for individual analyses using five or more outcomes (specifically, *SI Appendix*, Tables S7 and S8), noting there is no consensus on exactly how many hypotheses are required for MHT, but there are sufficient outcomes in these tables to warrant using Q-values.

Data, Materials, and Software Availability. Anonymized data and STATA do-files to replicate the analyses can be accessed at OSFHome via the following link: https://osf.io/42hrz/ (56).

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