Media Bias in Portrayals of Mortality Risks: Comparison of Newspaper Coverage to Death Rates, 1999-2020.

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Abstract

Objective. To assess how media coverage of different mortality risks compares to objective measures of deaths from each risk.

Methods. We gathered data on 14 mortality risks including monthly deaths within the United States from CDC Wonder, produced by the Centers for Disease Control and Prevention, and 823,406 articles about these risks from major US newspapers maintained by LexisNexis. We ran regression analyses comparing counts of deaths and media coverage longitudinally and qualitatively analyzed the articles using natural language processing tools.

Results. From 1999 to 2020, there was a major disconnect between the deadliest risks and those that were most covered by the media. While fluctuations in media coverage were associated to fluctuations in deaths, only 1.7-2.8% of the media coverage is explained by the death rate. Qualitative analysis revealed that the content of these articles varied substantially, with chronic illnesses described as individual challenges with neutral tone and sensational risks as collective problems with more negative tone.

Conclusion. To come to a more accurate depiction of the mortality risks facing the US population and how to mitigate these risks, media organizations should re-evaluate and update their focus on different risks and health practitioners should be made aware of existing biases in media coverage.

Keywords: Mass media; Mortality risks; Linear mixed models; Autoregressive distributed lag models; Health communication; and Risk communication

"News organizations...have great power to send a message that people should be generally alarmed by something, simply by covering it relentlessly." – Greg Sargent

"The news and the truth are not the same thing." – Walter Lippmann

1 Introduction

It is perhaps a sad fact of life that we humans are not gods. We are mortal and have finite attention and resources to invest in avoiding the many risks that threaten our mortality. Unfortunately, we collectively are far from optimal in allocating those scarce resources. For example, consider the risks that plague the United States. Here, chronic diseases lead to 7 out of every 10 deaths each year, but most of these could be prevented with proper behavior such as eating well, exercising, avoiding tobacco and excessive drinking, and getting regular health screenings [1]. While the US spends a considerable amount on health care—roughly $4.3 trillion in 2021, 18.3% of the gross domestic product [2]—only a small fraction of this spending goes to preventative care [3]. This lack of funding reflects a considerable mismatch between the value of preventing these diseases and the amount that we are currently investing in preventative measures [4]. What can account for this mismatch? Structural issues such as poverty [5] and cultural barriers including stigma toward treatments [6] explain some challenges individuals face; however, the ubiquitous nature of these health risks suggests other factors also play a role in shaping people's prevention behaviors. Here we investigate how biases in media coverage of mortality risks may present a distorted image of the mortality risks threatening society.

Many articles assess how media coverage connects to objective measures of mortality risks [7, 8, 9, 10]. In general, this work shows a large disconnect between these measures with media coverage over-representing some risks and under-representing others. This coverage may impact people's perception of the world and subsequent behavior; for example, scholarly work demonstrates similar disconnects between objective measures of risks and people's beliefs and collective risk-prevention actions [10, 11]. While providing important insights, these analyses are limited. They are largely crossectional and limited to assessing the counts rather than focusing on the content of coverage. We expand on this research by including longitudinal and qualitative analysis. To understand the importance of these methods, consider how bias may emerge in media coverage of different risks.

News organizations maintain a great deal of latitude in the topics they choose to cover, the facts they present from those topics, and how they frame those facts. Each of these choices can impact how credulous readers understand the world. For example, consider two hypothetical articles: one about the genetic determinants of cancer framed around an individual's tragic story and a second on how exercise and diet can mitigate heart disease, framed as a set of tips for healthier living. While both these articles may present empirically accurate information, they depict opposing perspectives about the amount of control individuals have over their health. When media organizations collectively cover certain risks more than others, focus on a subset of facts about those risks, and frame those facts in particular ways, they present a distorted perspective of reality that may influence people's perceptions and behaviors.

There are well-developed theories that help to make sense of how media may impact consumers' understanding of the world [12, 13]. Agenda-setting theory, for example, suggests that media prioritizes certain issues, thereby influencing the public's perception of what is important [14, 15, 16]. Under the current framework, agenda-setting works at the topic level, and its impacts may expand over time, a notion grounded in cultivation theory, which argues that prolonged engagement with media content is especially important for shaping perceptions [17, 18, 19]. Based on these theories, our longitudinal analysis provides insights both by allowing us to assess how changes in mortality rates correspond to changes in coverage (distortions in agenda-setting) and by assessing the stability of that coverage across time (prolonged cultivation). Framing theory focuses on the qualitative aspects of media content, suggesting that the way information is presented can significantly influence audiences' interpretation and understanding [20, 21, 22]. For health risks, two important frames to consider are how much the article focuses on the individual versus the collective and how threatening and negative they describe risks. If articles present risks in collective frames, they may highlight community or policy solutions, whereas when they use more individual framings, they suggest that risks do not need collective solutions. Additionally, when articles describe a risk as threatening and negative, they suggest it is an issue of greater concern. We consider these frames in our qualitative analysis.

In summary, this paper seeks to investigate distortions in media coverage of mortality risks. We assess distortions in topics (agendas) and qualitative framing, and we analyze a longitudinal period of 20 years to provide insight into time-trends within this coverage.

2 Methods

Risks: We selected a diverse set of risks for this analysis including six chronic diseases that were responsible for most deaths within the United States (heart disease, cancer, strokes, chronic lower respiratory disease, Alzheimer's, and diabetes), four more sensational risks that we expected to be more common in the media (homicide, suicide, overdose, and terrorism), and four other major causes of death that fall somewhere between the chronic and the sensational (traffic accidents, influenza, sexually transmitted disease, and pandemics/COVID-19).

Media Coverage: We identified four outlets (Star Tribune, New York Times, USA Today, Tampa Bay Times) that were both within the top ten US newspapers by circulations and had stable coverage within the LexisNexis database from 1999 to 2020. To select articles relevant to each mortality risk, we generated comprehensive sets of keywords tailored to each risk (See Supplementary Table S1). We then queried Lexis Nexis using these keywords, running separate queries for each newspaper and year resulting in a total of 823,406 articles across all risks. We combined the number of newspaper articles across journals to arrive at monthly counts of media coverage for each risk.

Mortality Rates: To identify the mortality rates associated with each risk, we utilized data from The Underlying Cause of Death database produced by CDC Wonder [23]. These data are based on death certificates from U.S. residents with each certificate identifying a single underlying cause of death. For this analysis, we looked across all demographics and locations to arrive at counts of mortality rates by date (month and year) and risk. We supplemented these data for pandemics, using the COVID Data Tracker also produced by the CDC [24], and for Terrorism using the Global Terrorism Database [25].

Longitudinal Analysis: We Winsorized the top and bottom 1% of monthly counts by each risk (accounting for extreme outliers by replacing them with the datapoint at each respective quantile) and we log transformed the modified counts. Finally, we replaced outliers from Tampa-Bay Times for the year 2019, when there were unusual sharp surges in mentions of a few risks, with the average of those risks from 2018 for that publication, and we subtracted terrorism deaths from the homicide counts to avoid double counting.

Different longitudinal analyses offer unique insights. For example, analyzing leveled data may be useful to assess if long-term trends in mortality rates are associated with long-term trends in media coverage; whereas assessing the relationship between the deseasonalized, differenced data provides insight into whether short-term changes in media-coverage correspond to short term changes in deaths. Additionally, including lagged terms in the regressions is necessary if there is a delay between changes in mortality rates and changes in media coverage. Finally, monthly data may prove to be too short of an interval or fall prey to dynamic seasonality, so looking at yearly trends may also be useful. We thus ran and report four sets of regressions (1) A multi-level regression with monthly mortality rates predicting leveled monthly media coverage with random intercepts and slopes for each risk. (2) The same multi-level regression with the deseasonalized and differenced data. (3) Autoregressive distributed lag models using both leveled and differenced data, ran separately for each risk. (4) The same regressions as 1-3 but with yearly data rather than monthly.

Qualitative analysis: We sampled 110 articles from each risk (5 per year) to be analyzed qualitatively. We were interested in the presented facts about the causes of the risk-factor along with mitigation strategies. We were also interested in how each of these facts were framed: whether the focus was on individuals or collectives as well as the sentiment of the article's description. With these aims in mind, we developed a prompt for

GPT-4—a large language model that performs remarkably well on a variety of tasks akin to this coding exercise [26]—to code the article on these dimensions (See Appendix S1.3). We provide qualitative insight into these articles based on this coding, and we supplement this with a more typical sentiment analysis approach [27] to assess longitudinal trends in the descriptions of these risks.

Our analysis plan was pre-registered: `https://doi.org/10.17605/OSF.IO/MR2AY`. See minor divergences in the Appendix S1.6. We report the results for all analyses conducted such that there are no "file-drawer" analyses.

3 Results

First, we report the number of articles and deaths by risks in Table 1. This table illustrates massive inequality in the correspondence between mortality rates and news coverage for different risks ranging from one article per 323 deaths from heart disease to 36 articles for every death from terrorism. Because pandemics/COVID-19 and terrorism experienced most of their deaths within a very short interval, we analyze these risks separately in all subsequent analyses. Additionally, we limit our data from 1999 to the end of 2019 because news coverage was dramatically different throughout the pandemic.

Risk	**Articles**	**Deaths**	**Articles to Deaths**
Heart Disease	48,024	15,499,612	1:323
Respiratory Diseases	15,282	3,064,049	1:200
Cancer	132,016	12,644,869	1:96
Stroke	41,433	3,184,602	1:77
Alzheimer's	27,026	1,872,576	1:69
Diabetes	25,395	1,674,724	1:66
Influenza	20,264	1,257,088	1:62
Overall	**823,406**	**42,879,844**	**1:52**
Traffic Accidents	28,534	956,960	1:34
Overdose	41,412	892,857	1:22
Suicide	60,913	838,850	1:14
STDs	40,320	210,774	1:5
Pandemics	92,295	385,666	1:4
Homicide	127,383	393,756	1:3
Terrorism	123,109	3,461	36:1

Table 1: Counts of articles and deaths for each risk from 1999 to 2020. The last column displays the ratio of articles to deaths for each risk.

To understand how changes in mortality rates correspond to changes in media coverage, we plotted both sets of time series for each risk used in our main analysis in Figure 1 panel A (See SI Figure S1 for pandemics/Covid-19 and Terrorism plot, and Figure S2-S3 for alternative visualizations). For some risks (e.g., homicide, suicide), the media mentions are far higher than the death rate whereas for others (e.g., heart disease, respiratory disease), the deaths outpace the media mentions. This illustrates the unequal media coverage for these risks with some receiving far more news coverage than others. Panel B indicates that these unequal ratios are largely stable over time. Additionally, these plots suggest that there may be associations between these measures. To statistical assess these, we next report the results from our modeling.

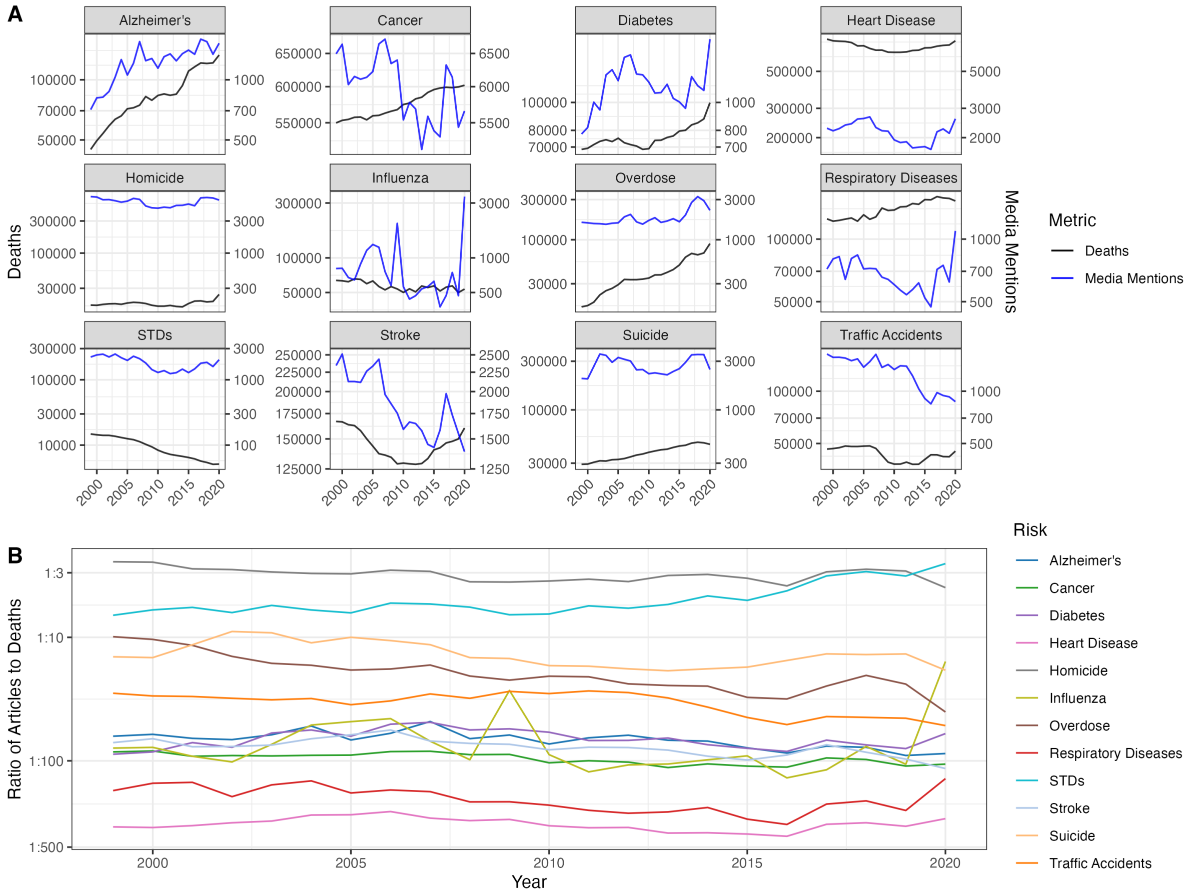

Figure 1: (Panel A) Annual deaths (black) and media mentions (blue) of twelve risks from 1999 to 2020. Note that the y-axes are scale free to highlight trend within each series; however, in each plot, the media mentions axis is 10x the death axis. (Panel B) The ratio of media mentions to deaths for each risk on a log scale stayed relatively stable over this time period.

We begin with a multi-level regression on the leveled data fitted by REML, using Satterthwaite's method for t-tests with the LMER package in R [28]:

$$y_{ij} = (\beta_0 + u_j) + (\beta_1 + v_j)x_{ij} + f_{\text{month}} + \epsilon_{ij} \tag{1}$$

In this model, monthly deaths from a risk (x_{ij}, i indicating month and j indicating the risk) predict monthly media mentions (y_{ij}) along with random intercepts (u_j) and slopes

(v_j) for each risk and a monthly dummy (f_{month}) to account for seasonality. The fixed effect of deaths was positive and significant ($b = 0.38$, $p = 0.004$) and the random intercepts and slopes allowed the full model to significantly outperform the model with only fixed effects ($p < 0.001$, See also Supplemental Tables S2-S3). Collectively, these results indicate that the media is much more likely to cover some mortality risks than others; when there are more deaths from a risk, the media is more likely to cover it compared to time periods with fewer deaths from that risk; and the relationship between deaths and media coverage varies from risk to risk. To visually understand these relationships, we plotted the random effects in Figure 2. This figure illustrates how for all risks except for cancer and respiratory disease, the relationship between deaths and media mentions is positive even though the risks vary significantly in their number of deaths and media coverage.

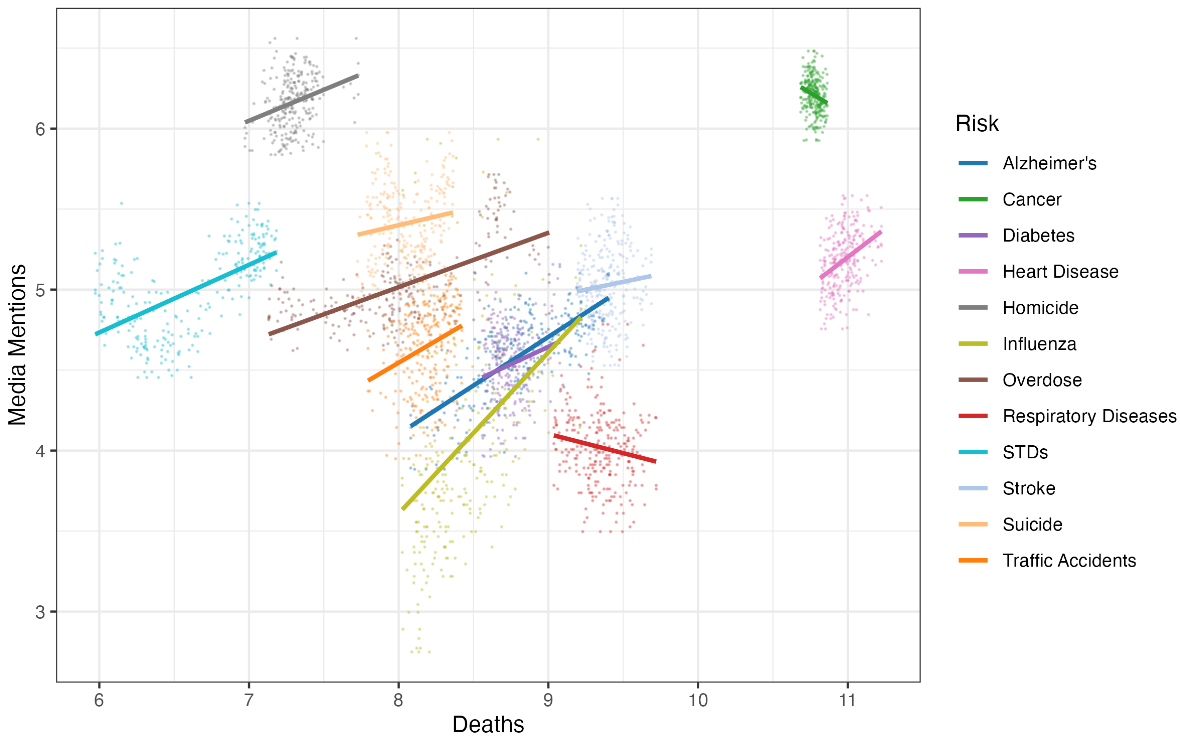

Figure 2: Random effects of log monthly deaths on log monthly media mentions for each risk. Most of the slopes are positive suggesting that in months when a risk results in more deaths, the media is more likely to cover that risk.

We ran a similar regression on the differenced and deseasonalized mortality ($\hat{x}_{ij}$) and media mentions ($\hat{y}_{ij}$):

$$\hat{y}_{ij} = (\beta_0 + u_j) + (\beta_1 + v_j)\hat{x}_{ij} + \epsilon_{ij} \tag{2}$$

Once more, we found significant results for the random slope model in comparison to a model with only fixed effects ($p < 0.001$). Again, the fixed effect was significant and positive ($b = 0.42$, $p = 0.014$, See also Supplemental Tables S4-S5). This implies that on months when there were significantly more deaths than the previous month due to a given risk, these newspapers discuss it in more of their articles, though the random slopes suggest that this relationship varies from risk to risk.

Our analyses thus far have been contemporaneous, but it is possible that mortality information takes some time to reach the media. For this reason, we also ran autoregressive distributive lag models with lagged media mentioned and mortality rates for each risk included in the model. We ran separate regressions for each risk with both the leveled and differenced data, comparing full models with lagged mortality information to models without these terms. For the models with the leveled data which included monthly dummies (Supplementary Table S6), we found that including lagged mortality information resulted in improved model fit at typical significance thresholds for three of the 12 risks (Supplementary Table S7). Collectively, these models were jointly significant ($p = 0.003$, Fisher's method for combining independent p-values). Looking at the differenced and deseasonalized data, these models were again significant at typical thresholds for four of the 12 risks (Supplementary Tables S8-S9), producing a jointly significant result ($p < 0.001$).

While we found significant relationships between deaths and media mentions across risks, it is important to note that the death information only explains about 2% of the number of media mentions a given risk receives (leveled mean change in $R^2 = 0.017$, differenced mean change in $R^2 = 0.028$, both in comparison to models without death information). This is a small change in explanatory power that demonstrates only a weak connection between these measures. Finally, following our pre-registration, we ran similar sets of models on the annual rather than monthly data as an additional robustness check and found very similar results (See Supplemental Analysis S1.1). While these data demonstrate how media coverage of risk factors and risk-driven mortality are largely disconnected, it is important to note that the risks included in the primary analysis are perennial problems that have plagued humanity throughout the entire period of analysis. If one considers more novel risk factors (e.g., pandemics/COVID-19 and terrorism), the media is initially very responsive to these threats. Still, eventually they too become self-perpetuating stories that are largely unexplained by changes in the death rate (see Appendix S1.2).

Next, we describe our qualitative analysis. We were primarily interested in the extent to which the articles discuss facts related to the causes and mitigation strategies for risks and how the article framed these facts in terms of effectiveness, emphasis on individuals compared to collectives, and sentiment. Using output from GPT-4, we found that the articles varied substantially across risks in all these dimensions. First, we describe differences in the facts selected within articles (See Appendix S1.4 for more details).

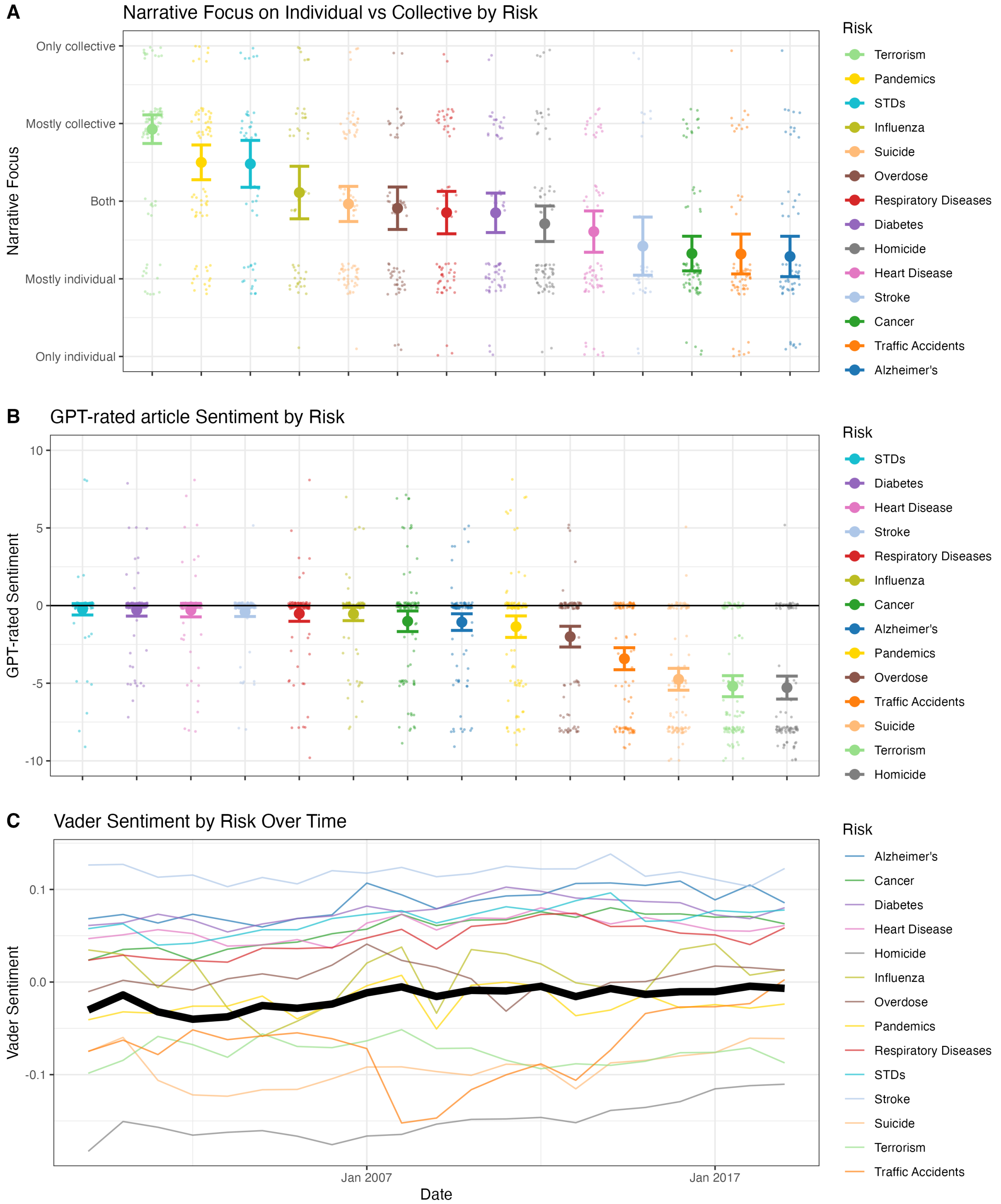

Figure 3: Panel A depicts article framing on a five-point scale from only focused on the individual to only focused on the collective. Panel B shows GPT-4 sentiment (-10 very negative to 10 very positive). For these panels, the large dots and error bars show means and 95% confidence intervals, and the small dots represent individual articles. Panel C shows mean yearly sentiment, as scored by VADER, for the entire study period for each risks, with the dark black line showing the overall mean sentiment. This figure illustrates how chronic risks were often talked about with a more individual focus and neutral tone, whereas sensational risks were more collectively focused and negative in tone, with the differences in sentiment being largely stable over time.

When discussing risks' causes, articles primarily pointed to environmental and lifestyle factors, though this differed across risks. For example, chronic respiratory disease was generally described as caused by environmental factors, diabetes as driven by lifestyle choices, and homicide as a mixture of these two. To mitigate the risk factors, the articles brought up numerous methods that can be grouped into three categories: policy, behavioral, and technological solutions. We found that articles about chronic diseases discussed mostly behavioral and technological mitigation strategies, whereas more sensational risks including overdose, homicide, and suicide were all more focused on policy solutions.

Articles also varied substantially in their framing of these facts (Figure 3). In general, chronic diseases were often presented with more of an individual focus, with the media offering ways individuals could avoid them. In contrast, more sensational risks were much more focused on the collective implications for broader society and policy solutions (Figure 3, panel A). Similar groupings emerge in regard to the sentiment of these articles with sensational risks often described with much more negative emotions than chronic illnesses, which are generally presented in a neutral manner (Figure 3, panel B). Looking at the sentiment ratings from VADER, we find that these trends are largely stable across the 20-year period analyzed in this study. To illustrate this stability, we plot mean annual sentiment for all risks in Figure 3, panel C. Please refer to the Appendix S1.4 and S1.5 for a much more detailed description of these results.

Finally, to connect our qualitative and quantitative analyses, we briefly compare the mean sentiment and narrative focus by risk (N = 14) to the ratios from Table 1 and the random slopes from our mixed regression. We found risks with more articles to deaths are also covered in a more negative tone ($\rho = -0.60, p = 0.025$) and are more likely to be framed in a collective manner ($\rho = 0.62, p = 0.020$). In contrast, neither sentiment ($\rho = 0.27, p = 0.390$) nor collective vs individual framing ($\rho = -0.03, p = 0.931$) is related to the slope adjustments from our mixed regressions. These patterns along with their relative stability over time suggests that there are different forms of bias underlying media portrayals of mortality risks.

4 Discussion

Like prior studies [7, 8, 9, 10], we found a significant gap between the mortality risks facing the US and the mortality risks that are covered in the news. This mismatch occurs at multiple levels. Chronic illnesses as topics are relatively less covered compared to sensational risks, indicating how the news sets an agenda that prioritizes some risks over others [14, 15, 16]. Qualitative analysis revealed similar biases in framing, with chronic diseases being portrayed in a neutral tone and as individual-focused whereas sensational risks were more likely to be portrayed as negative and collective-focused. These framings offer a narrative that the sensational risks are more concerning and that community or policy solutions are necessary to avoid them and that such solutions are less necessary for chronic illnesses. Finally, longitudinal analysis revealed that the both distortions in framing and topic remained relatively stable from 1999-2020, an important result under the framework of cultivation theory [17, 19].

Despite these distortions, we also identified a significant though weak relationship between changes in mortality rates and changes in media coverage. While other factors explain the lion's share of variance in coverage, the media is at least somewhat reflective of changes in objective patterns for these risks. Indeed, when we investigated two more novel risks that could be viewed as exogenous shocks to the system during this period, terrorism and pandemics/COVID-19, we found that the media was much more initially responsive to the emerging threats. Perhaps newspapers are focusing on, well, news and so are less motivated to discuss perennial mortality risks. While this may be the case, we found similar distortions for sensational risks that plagues the US since before the start of the study (e.g., homicide, suicide, drug overdose), suggesting that a focus on novelty only explains part of this disconnect.

4.1 Limitations

Our study comes with limitations regarding our sample and analytical techniques. While our dataset is quite large, with comprehensive coverage of four of the largest US newspapers during the study interval, it is important to note that news coverage makes up only a tiny portion of people's media-diets [29]. Individuals get most of their media from other outlets, and future work could benefit by quantifying the distortions of mortality risks in other non-news data. Additionally, our work is observational and cannot speak to causal patterns between these measures. News organizations may simply be catering to consumer's preferences, showing readers stories that they will find more engaging, with evolutionary and cultural pressures pushing individuals to be more attuned to the sensational risks. To the extent that this is true, changing media coverage to more accurately reflect mortality rates in the real world may not be very influential in updating people's perceptions and behaviors. Furthermore, there may be confounding variables that drive the modest relationship between mortality rates and media coverage that we observed in this observational study. Confounders seem plausible for one risk, overdose from illicit drugs, because when a population is more aware of a substance people may be more likely to indulge in it and the media may also be more likely to cover it. Still, it is more challenging to identify plausible confounders for the vast majority of our risks (e.g., Heart disease, Cancer, Stroke, etc.), and reverse causality also seems unlikely for these. Finally, we did not investigate how these measures correspond to behavioral patterns, a limitation that should be addressed in future studies. We view this as a critical next step in understanding the impacts of distorted media coverage on population health.

4.2 Public Health Implications

While we did not include belief or behavioral outcomes in our analysis, we would like to briefly speculate about the potential consequences of our findings. First, individuals often rely on simple heuristics when making decisions regarding risks [30]; these are strategies that often lead to good decisions, particularly in environments that humans evolved in [31]. Still, media distortion may lead individuals to place disproportionate weight on the more heavily covered risks. For example, by relying on the availability heuristic, individuals may believe these over-covered risks are more common [32] and thus problematic and worthy of attention. As a consequence, people may spend *less time and effort* on preventing the less-covered chronic risks that are more prevalent and more easily preventable. Similarly, the framing of articles may impact peoples' beliefs about these risks [20, 21], making consumers think that collective solutions are less necessary and helpful.

Beliefs about mortality risk may impact other seemingly unrelated behaviors as well. For example, when individuals believe they are at risk of death due to factors that lie outside of their control, they may rationally place less value in deferred rewards [33]. As a consequence, they may perform a suite of more present-oriented behaviors, saving less for their future and ultimately realizing poorer health outcomes. There is empirical support for this behavioral hypothesis [33], and research that investigated risk perceptions found that beliefs about mortality risk are only weakly tied to the actual threats people face [34, 35]. Perhaps the media distortions identified here may also impact people's perceptions and behaviors.

In conclusion, we identified significant distortions in media presentation of mortality risks with newspapers significantly over-representing more sensational risks and significantly under-representing other risks. In addition to biases in representation, we found biases in the framing of these articles with coverage of sensational risks being more negative and focused on the collective solutions than coverage of chronic risks. While there is a significant relationship between objective measures of mortality rates and media coverage, this relationship is quite weak. Future work should expand on these findings by incorporating behavioral outcome measures and health practitioners should be made aware of the distortion in media coverage. Ultimately, understanding these distortions is crucial for improving public awareness and informing media literacy initiatives, ensuring a more accurate and balanced perception of mortality risks.

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S1 Appendix

This file contains:

Tables: S1 - S9

Figures: S1 – S11

Supplemental analysis: Annual Data S1.1

Supplemental analysis: COVID-19 and Terrorism as exogenous shocks S1.2

GPT Prompt: For qualitative analysis S1.3

Supplemental analysis: Qualitative insight with GPT S1.4

Supplemental analysis: Sentiment analysis using VADER S1.5

Pre-registration: Divergences and Link S1.6

Supplemental References: S1.7

Risk	Keywords in Query
Alzheimer's	Alzheimer's OR Alzheimer OR dementia OR cognitive decline OR memory loss OR neurodegeneration OR amyloid plaques OR tau tangles OR brain health
Cancer	cancer OR carcinoma OR malignancy OR tumor OR neoplasm OR chemotherapy OR radiation therapy OR immunotherapy OR oncology OR metastasis OR biopsy OR mammography
Chronic Respiratory Disease	chronic respiratory disease OR chronic obstructive pulmonary OR COPD OR asthma OR pulmonary fibrosis OR cystic fibrosis OR sleep apnea OR occupational lung disease OR pulmonary hypertension OR bronchitis OR emphysema OR (air pollution AND respiratory health)
Pandemics	COVID-19 OR coronavirus OR SARS OR epidemic OR pandemic OR MERS
Diabetes	diabetes OR insulin OR blood sugar levels OR glucose tolerance OR hbA1c OR hyperglycemia OR hypoglycemia
Heart Disease	Heart disease OR cardiovascular disease OR Coronary artery disease OR Heart failure OR Cardiomyopathy OR Arrhythmia OR dysrhythmia OR Hypertension OR high blood pressure OR arteriosclerosis OR Heart attack OR myocardial infarction OR chest pain OR Peripheral artery disease OR Cardiac arrest
Homicide	homicide OR murder OR manslaughter OR violent crime OR intentional killing
Influenza	influenza OR flu OR H1N1
Overdose	overdose OR substance abuse OR drug abuse OR opioids OR addiction OR harm reduction
Sexually Transmitted Diseases	sexually transmitted diseases OR STDs OR STD OR sexually transmitted infections OR STIs OR STI OR chlamydia OR gonorrhea OR syphilis OR human papillomavirus OR HPV OR genital herpes OR HSV-1 OR HSV-2 OR HIV OR AIDS OR trichomoniasis OR hepatitis B OR hepatitis C OR pubic lice OR scabies
Stroke	stroke OR cerebrovascular accident OR transient ischemic attack OR brain attack OR thrombosis OR embolism OR aneurysm OR (blood clot AND brain)
Suicide	suicide OR self-harm OR suicidal
Terrorism	terrorism OR terrorist OR counterterrorism OR radicalization OR extremism OR suicide bombings
Traffic Accidents	traffic accident OR car crash OR car accident OR road traffic injury OR motor vehicle accident OR pedestrian collision OR bicycle accident OR drunk driving OR hit and run OR vehicular manslaughter

Table S1: Keywords within queries used to identify relevant articles on LexisNexis.

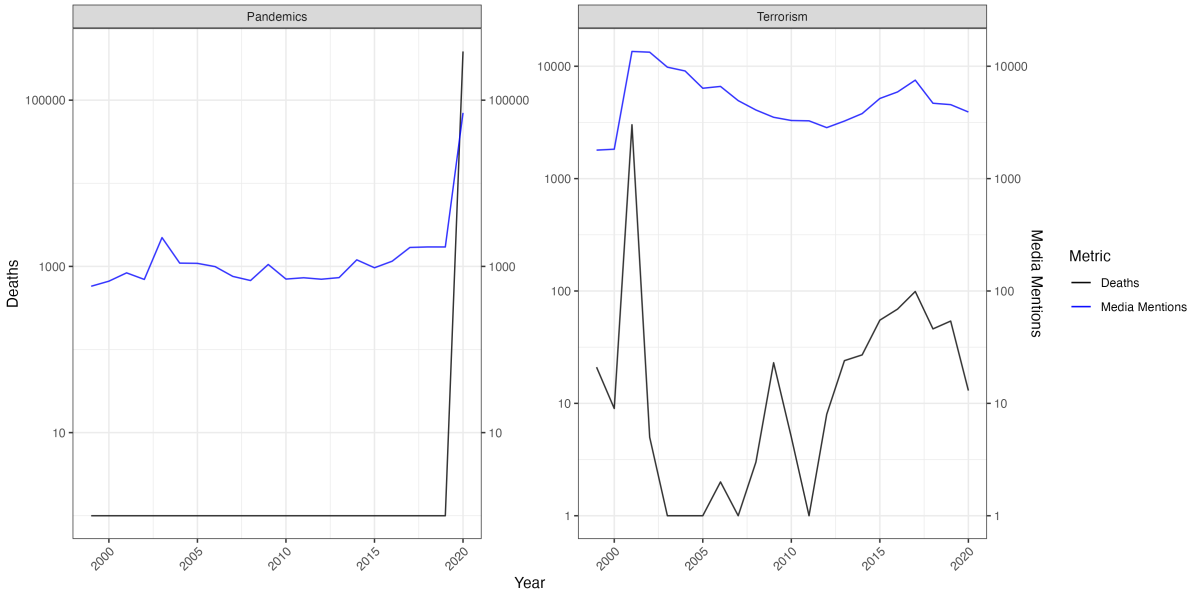

Figure S1: Deaths and media mentions related to Pandemics (COVID-19) and Terrorism.

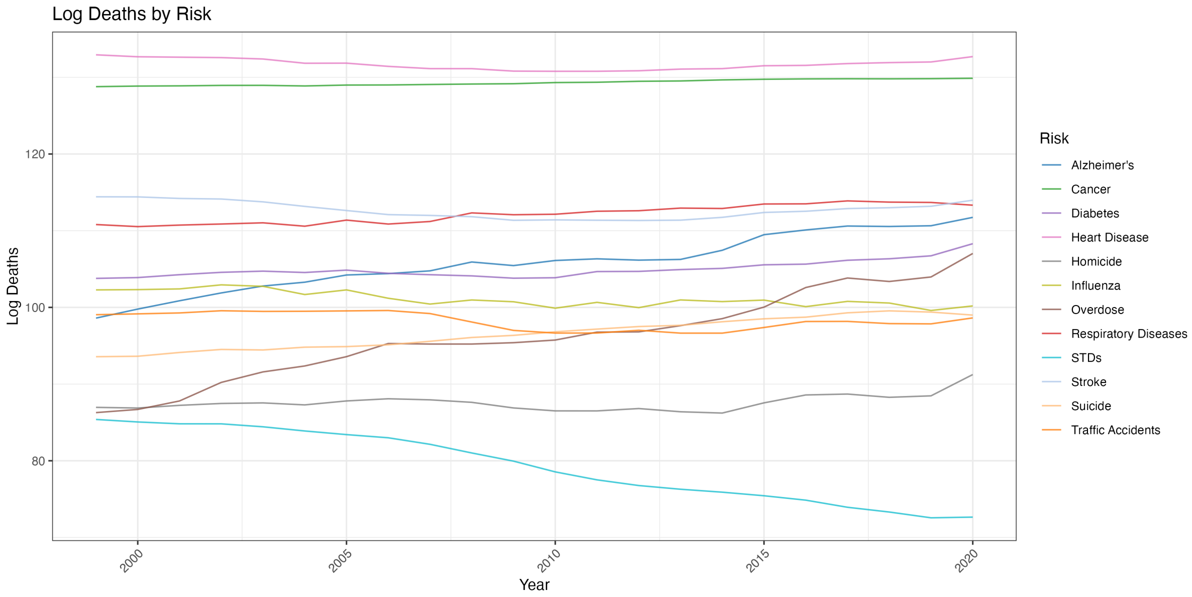

Figure S2: Log annual death rate for all risks included in primary analyses.

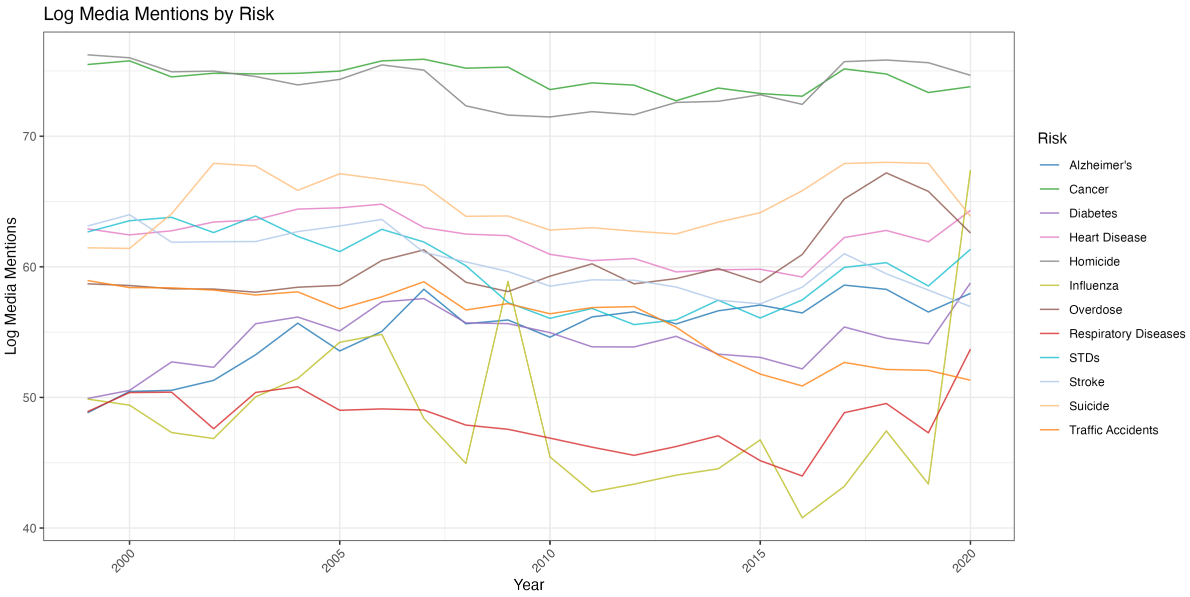

Figure S3: Log annual media mentions for all risks included in primary analyses.

Table S2: Summary output of fixed effects from model one, a mixed model with random intercepts and slopes of monthly deaths predicting monthly media mentions for different risks.

Term	**Estimate**	**SE**	**T statistic**	**DF**	**p**
(Intercept)	1.707	1.020	1.674	8.714	0.130
Log Deaths	0.377	0.101	3.729	9.863	0.004
FMonth02	-0.008	0.024	-0.335	3143.271	0.737
FMonth03	0.046	0.023	1.994	3135.558	0.046
FMonth04	0.039	0.024	1.638	3145.932	0.101
FMonth05	0.062	0.024	2.578	3140.237	0.010
FMonth06	0.046	0.024	1.895	3069.634	0.058
FMonth07	0.028	0.024	1.143	3071.608	0.253
FMonth08	0.036	0.024	1.456	3075.390	0.145
FMonth09	0.015	0.025	0.631	3073.554	0.528
FMonth10	0.089	0.024	3.728	3137.763	< 0.001
FMonth11	0.024	0.024	1.011	3146.046	0.312
FMonth12	0.020	0.023	0.874	3138.075	0.382

Table S3: Summary output of random effects for model one, a mixed model with random intercepts and slopes of monthly deaths predicting monthly media mentions for different risks.

Risk	**Intercept Adjustments**	**Slope Adjustments**
Alzheimer's	-2.48	0.23
Cancer	4.32	-0.36
Diabetes	-1.30	0.09
Heart Disease	-3.60	0.26
Homicide	2.53	-0.12
Influenza	-6.24	0.64
Overdose	0.59	-0.04
Respiratory Diseases	3.60	-0.52
STDs	0.52	0.04
Stroke	0.90	-0.12
Suicide	2.06	-0.18
Traffic Accidents	-0.88	0.08

Table S4: Summary output of fixed effects from model two, a mixed model with random intercepts and slopes of monthly deaths predicting monthly media mentions for different risks using differenced and deseasonalized measures.

Term	**Estimate**	**SE**	**T statistic**	**DF**	**p**
Intercept	0.001	0.003	0.22	3,151	0.823
Differenced, deseasonalized monthly deaths	0.420	0.148	2.831	14	0.014

Table S5: Summary output of random effects for model two, a mixed model with random intercepts and slopes of monthly deaths predicting monthly media mentions for different risks, using differenced and deseasonalized data.

Risk	**Intercept Adjustments**	**Slope Adjustments**
Alzheimers	0	-0.14
Cancer	0	0.01
Diabetes	0	0.02
Heart	0	0.09
Homicide	0	-0.21
Influenza	0	0.71
Overdose	0	-0.03
Respiratory Diseases	0	-0.34
STDs	0	-0.14
Stroke	0	-0.21
Suicide	0	-0.18
Traffic Accidents	0	0.41

Table S6: Model output from distributed lag regressions with lagged media mentions and death rate predicting monthly media mentions. Note, there was also a monthly dummy in these regressions. The summary provides an F value for models with 18 coefficients and 230 degrees of freedom, along with adjusted R squared values. The remaining columns display coefficients and p-values, * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$. The full model for each risk is presented in this equation:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_{-1i} + \beta_3 x_{-2i} + \beta_4 x_{-3i} + \beta_5 y_{-1i} + \beta_6 y_{-2i} + \beta_7 y_{-3i} + f_{month} + e_i$$

Where y_i represents the media mentions (and lagged terms), x_i represents mortality information (and lagged terms), f_{month} is a monthly dummy variable. For the lags, D stands for deaths and MM for media mentions.

Risk	**Summary**	**Intercept**	**Deaths**	**D Lag1**	**D Lag2**	**D Lag3**	**MM Lag1**	**MM Lag2**	**MM Lag3**
Alzheimer's	F=27.2, Adj. $R^2 = 0.64$	-0.35	0.12	0.52	-0.87**	0.48*	0.33***	0.15*	0.14*
Cancer	F=12.2, Adj. $R^2 = 0.44$	9.51***	-0.07	-0.46	-0.17	0.05	0.34***	0.19**	0.06
Diabetes	F=14.3, Adj. $R^2 = 0.48$	-0.27	0.64	-0.52	0.99*	-0.97*	0.36***	0.24***	0.18**
Heart Disease	F=17.9, Adj. $R^2 = 0.54$	-2.11	0.69*	-0.76	0.33	0.03	0.41***	0.19**	0.18**
Homicide	F=20.8, Adj. $R^2 = 0.58$	0.30	0.18	0.21	-0.14	-0.11	0.56***	0.05	0.18**
Influenza	F=37.1, Adj. $R^2 = 0.71$	-0.77	1.17***	-0.50	-0.06	-0.49	0.61***	0.15*	0.13*
Overdose	F=32, Adj. $R^2 = 0.68$	0.42*	0.12	-0.16	0.13	-0.02	0.41***	0.21**	0.18**
Respiratory Diseases	F=11.8, Adj. $R^2 = 0.43$	2.00	-0.06	-0.21	0.45	-0.29	0.30***	0.23***	0.24***
STDs	F=32.5, Adj. $R^2 = 0.69$	0.35	0.30	0.04	-0.11	-0.17	0.39***	0.20**	0.24***
Stroke	F=37.9, Adj. $R^2 = 0.72$	-0.84	-0.57	0.09	0.04	0.63	0.32***	0.26***	0.25***
Suicide	F=20.8, Adj. $R^2 = 0.58$	0.80	0.35	-0.32	0.27	-0.30	0.41***	0.18**	0.26***
Traffic Accidents	F=26.3, Adj. $R^2 = 0.64$	-0.95	0.85**	-0.04	-0.93**	0.33	0.43***	0.25***	0.17**

Table S7: P-values from ANOVAs that assess whether including three lagged terms for mortality increased model fit relative to a base model without these terms. For each risk the model was: $y_i = \beta_0 + \beta_1 x_i + \beta_2 x_{-1i} + \beta_3 x_{-2i} + \beta_4 x_{-3i} + \beta_5 y_{-1i} + \beta_6 y_{-2i} + \beta_7 y_{-3i} + f_{month} + e_i$ Where y_i represents the media mentions (and lagged terms), x_i represents mortality information (and lagged terms), f_{month} is a monthly dummy variable.

Risk	**P-value**
Alzheimer's	0.031
Cancer	0.760
Diabetes	0.056
Heart	0.320
Homicide	0.549
Influenza	0.001
Overdose	0.955
Respiratory Diseases	0.735
STDs	0.615
Stroke	0.084
Suicide	0.546
Traffic Accidents	0.007

Table S8: Model output from regressions with lagged media mentions and death rate predicting monthly media mentions with deseasonalized and differenced data. The summary provides an F value for models with 7 coefficients and 240 degrees of freedom, along with adjusted R squared values. The remaining columns display coefficients and p-values, * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$. The full model for each risk is presented in this equation: $y_i = \beta_0 + \beta_1 x_i + \beta_2 x_{-1i} + \beta_3 x_{-2i} + \beta_4 x_{-3i} + \beta_5 y_{-1i} + \beta_6 y_{-2i} + \beta_7 y_{-3i} + e_i$ Where y_i represents the deseasonalized, differenced media mentions (and lagged terms) and x_i represents deseasonalized, differenced mortality information (and lagged terms). For the lags, D stands for deaths and MM for media mentions.

Risk	**Summary**	**Intercept**	**Deaths**	**D Lag1**	**DLag2**	**DLag3**	**MM Lag1**	**MM Lag2**	**MM Lag3**
Alzheimer's	F=17.1, Adj. $R^2 = 0.3$	0.01	-0.02	0.51*	-0.43	-0.13	-0.61***	-0.39***	-0.21***
Cancer	F=14, Adj. $R^2 = 0.26$	0.00	0.42	-0.09	0.00	0.84	-0.56***	-0.33***	-0.27***
Diabetes	F=15.2, Adj. $R^2 = 0.28$	0.00	0.64	0.02	0.99*	-0.22	-0.59***	-0.34***	-0.15*
Heart Disease	F=13.7, Adj. $R^2 = 0.25$	0.00	0.55	-0.20	0.11	-0.28	-0.56***	-0.37***	-0.21***
Homicide	F=9.9, Adj. $R^2 = 0.19$	0.00	0.19	0.40*	0.27	0.17	-0.42***	-0.35***	-0.23***
Influenza	F=9.6, Adj. $R^2 = 0.19$	0.01	1.23***	0.77**	0.52	0.23	-0.35***	-0.18**	0.03
Overdose	F=11.1, Adj. $R^2 = 0.22$	0.00	0.11	0.04	0.08	0.14	-0.55***	-0.30***	-0.12
Respiratory Diseases	F=16.7, Adj. $R^2 = 0.3$	0.00	-0.05	-0.47	0.34	-0.63*	-0.61***	-0.31***	0.01
STDs	F=14.9, Adj. $R^2 = 0.27$	0.01	0.40	0.52*	0.49	0.45*	-0.61***	-0.40***	-0.18**
Stroke	F=16.1, Adj. $R^2 = 0.29$	0.00	-0.49	-0.55	-0.59	-0.27	-0.66***	-0.38***	-0.12
Suicide	F=14.7, Adj. $R^2 = 0.27$	0.00	0.27	-0.08	0.05	-0.67*	-0.58***	-0.40***	-0.16**
Traffic Accidents	F=15.6, Adj. $R^2 = 0.28$	-0.01	0.84**	0.79**	-0.19	0.05	-0.55***	-0.29***	-0.14*

Table S9: P-values from ANOVAs that assess whether including three lagged terms for mortality increased model fit relative to a base model without these terms with the deseasonalized and differenced data. For each risk the model was: $y_i = \beta_0 + \beta_1 x_i + \beta_2 x_{-1i} + \beta_3 x_{-2i} + \beta_4 x_{-3i} + \beta_5 y_{-1i} + \beta_6 y_{-2i} + \beta_7 y_{-3i} + e_i$ Where y_i represents the deseasonalized, differenced media mentions (and lagged terms) and x_i represents deseasonalized, differenced mortality information (and lagged terms).

Risk	**P-value**
Alzheimer's	0.019
Cancer	0.402
Diabetes	0.044
Heart	0.703
Homicide	0.152
Influenza	0.002
Overdose	0.945
Respiratory Diseases	0.120
STDs	0.088
Stroke	0.338
Suicide	0.107
Traffic Accidents	0.009

S1.1 Supplemental analysis with annual data

In the main text, we ran analyses on monthly data. While we found significant results, it is possible that information about deaths takes even longer to reach the media than the timeframe we analyzed (up to three months). Since we were concerned about this possibility, we had pre-registered analyses with the annual data as well and we report on those results here.

Model 1: Mixed model with random intercepts and slopes on leveled data. We ran a mixed level model of yearly deaths on yearly media mentions for each risks including random intercepts and slopes. Because we moved to a yearly timeframe, we no longer needed monthly dummies for this model. Formally, this model is represented below:

$$y_{ij} = (\beta_0 + u_j) + (\beta_1 + v_j)x_{ij} + \epsilon_{ij} \tag{S1}$$

Relative to a model with only fixed effects, including random intercepts significantly improved model fit ($p < 0.001$). Adding random slopes did not significantly improve the explanatory power of the model at typical levels of significance ($p = 0.582$), so we only include random intercepts in our final model. In this model, we found a significant fixed effect of deaths on media mentions ($B = 0.39, SE = 0.06, p < 0.001$). This means that in years when there were more deaths due to a risk, there were also more media coverage of that risk.

Model 2: Turning to the differenced data, we found that a mixed level model with random intercepts failed to converge likely due to the lack of variability for some of these risks. For this reason, we look only at OLS models for this analysis.

$$\hat{y}_i = \beta_0 + \beta_1 \hat{x}_i + \epsilon_{ij} \tag{S2}$$

We found a significant fixed effect of deaths on media mentions ($B = 0.57$, $SE = 0.25$, $p = 0.024$). This means that in years where there were relatively more deaths compared with the previous due to a risk, there was also more media coverage of that risk. The R^2 for this model was 0.020, which closely matches amount of variance in media mentions captured by deaths in the monthly data.

Model 3: Autoregressive model with lagged deaths and media mentions on leveled data. We ran autoregressive models with deaths and lags of deaths and media mentions predicting monthly media mentions for each risk using the leveled data. With this approach we found a significant result for two of the risks, and the joint p-value across all risks was marginally significant ($p = 0.043$). This suggests that deaths from a year prior were significantly associate with changes in media coverage. ehaverage change in

R^2 across all models was 0.05, again suggesting only a small relationship between these measures.

Model 4: Autoregressive model on differenced data. We ran autoregressive models with deaths and lags of deaths and media mentions predicting monthly media mentions for each risk using the differenced data. With this approach we again only found a significant result for one of the risks, and the joint p-value across all risks was not significant ($p = 0.32$). This suggests that deaths from a year prior did not significantly associate with changes in media coverage. The average change in R^2 across all models was 0.08.

S1.2 Supplemental analysis of pandemics/COVID-19 and terrorism as exogenous shocks

In the main text, we removed pandemics and terrorism from the dataset before running our models, because these two causes experienced substantially different mortality patterns than the others with the vast majority of deaths over a very short interval. In all of the other risks, we found a substantial mismatch between the death rate and media coverage, with changes in deaths accounting for only about 2% of the changes in media coverage. Perhaps this lack of coverage is a product of these risks being the perennial problems that have plagued humanity for centuries. Because chronic illnesses and things like homicide have been around for a long time, they may not be news-worthy and so the small changes in deaths each month (relative to absolute counts) may not be so important for driving news. In contrast, pandemics (including COVID-19) and terrorism experienced dramatic changes in deaths over the time period of interest, and so we might expect that the death patterns for these two risk factors might be far more important for driving media trends. To assess this possibility, we ran separate models for these two risk factors. Because these deaths occurred over a short interval, we do not Winsorize them before analysis and we only run analyses on the leveled data.

Looking at the plots for these risks (Figure S1), it is evident that the media begins talking much more about them after there has been substantially more deaths due to each risk factor. Media mentions of terrorism greatly increase around September 2001, and COVID-19 increased at the beginning of 2020. The explanatory value of the mortality rate greatly depends on how you model it. For example, looking at terrorism, relative to a null model with only a monthly dummy ($R^2 = 0.03$), a full model with the death rate and three lags of both the death rate and media mentions explains vastly more of the variance in media mentions ($R^2 = 0.83$). Still, a model without any death information but the same three lags of media mentions already explains most of this variance ($R^2 = 0.78$). The importance of lagged media mentions is displayed by the fact that after 2001, the mentions of terrorism in newspaper articles remained much higher than before 2001, throughout the rest of the analyzed period. For this reason, we can see how media coverage of terrorism greatly increased after the terrorist attacks on September 11th, 2001, and after these, the newspapers continued to focus on this risk factor.

Similar results are found for media coverage of pandemics and COVID-19. Relative to a null model with a monthly dummy ($R^2 = 0.01$), a full model with both deaths and lags of deaths and media mentions explains vastly more variance ($R^2 = 0.93$). Still, most of the variance is explained by a model that only has lags of media mentions ($R^2 = 0.91$). Again, this illustrates how when there are exogenous shocks, where a novel risk factor begins to plague a population, the media coverage also increases dramatically with those deaths; however, after this coverage has begun it seems to self-perpetuate.

S1.3 GPT Prompt

```
## Context ##
Your task is to perform content analysis of an article that
mentions [HEALTH RISK]. Focus on the how the article describes
causes, mitigation techniques, at risk populations, and other
characteristics of [HEALTH RISK]. You will be asked to describe
both the *facts* that are presented and how those facts are
*framed*.

## Article ##
[ARTICLE]

## Response ##
Select all that apply from provided list considering both what
is explicitly mentioned and what is implied. Answer format:
{"Focus": To what extent is this article about [HEALTH RISK]?
    Not at all, Mentions once, Slightly, Mostly, Entirely,
"Facts-Causes": Genetic, Environmental, Lifestyle, Not mentioned
    and not implied,
"Facts-Mitigation": Medication, Medical procedures, Diet, Exercise,
    Other behavior, Innovations/Technology, Policy, Community
    solutions, Not mentioned and not implied,
"Facts-Populations": Demographics of person with health risk or
    at-risk populations, e.g., Race = white, Gender = female,
    Age = young-adult, SES = poor, etc. If none are described say
    Not mentioned and not implied.
"Framing-Causes": How controllable are causes of [HEALTH RISK]
    described as? Single number from 0 (Not at all) { 100
    (Completely). If causes are not discussed say Not mentioned
    and not implied.
"Framing-Mitigation": How effective are mitigation strategies
    described as? 0 (Not at all) { 100 (Completely). If mitigation
    is not discussed say Not mentioned and not implied.
"Framing-Solutions": If the article discusses preventing or
    mitigating risk, is that discussion primarily focused on
    individual focused or collective solutions? Single number
    from 0 (Fully individual) to 100 (Fully collective). Can
    say Not mentioned and not implied.
```

```
"Framing-Populations": In general, is the narrative focused on
    Collective (reporting policy/statistics), the Individual
    (sharing a personal story or behavioral advice), or both?
    Only collective, Mostly collective, Both, Mostly individual,
    Only individual
"Sentiment": How positive or negative is description of [HEALTH
    RISK]? -10 Very Negative to 10 Very Positive,
"Threat": How threatening is description of [HEALTH RISK]?
    1 (Not at all) { 10 (Extremely)
}
```

S1.4 Supplemental qualitative analysis:

Our regression analyses with the monthly count data reflect how newspaper coverage of mortality risks as a topic correspond to actual deaths from each risk. With those analyses we found that there is a considerable mismatch between these measures, though a small portion of the variation in newspaper coverage can be explained by changes in the death rate. However, this coverage can also vary in the way that it covers each risk. For example, some coverage might focus on the causes of different mortality risks, whereas other coverage may focus on mitigation strategies; some articles may describe risks as an individual, as opposed to a collective, problem, and some may use more positive framings than others. Our existing analysis does not shed light into the content of articles related to different risks, and for this reason we also ran qualitative analysis on a sample of the articles.

We took an inductive approach to this qualitative analysis, reading through several dozen articles and scanning the literature to identify ways that the newspaper articles might vary in their coverage. We found several dimensions that we thought would both vary across risks and would provide useful insight into any biases present in the data. To begin, we noticed that the articles varied substantially in how much of the content was dedicated to discussion of the associated risk. For example, some articles were fully focused on a risk whereas others only mentioned it in passing. Second, we noticed that some of the articles discussed the causes of a mortality risk, focusing on different factors—e.g., environmental, lifestyle choices, and genetic influences—across risks, whereas others were silent on this issue. Similarly, some articles discussed risk mitigation strategies, and these too differed across risks with e.g., some providing behavioral advice and others discussing policy solutions. Fourth, we noticed that the articles varied in their framing of each of these, including how controllable they described the causes, how effective they described mitigation techniques, the individual vs collective nature of the narrative and solution strategies, the overall sentiment with either negative (e.g., story of someone who died of a risk factor) or positive (e.g., steps to live healthier in a new year) framings, and how threatening they described the risk. Finally, we noticed that articles often described population characteristics of those who were exposed to each risk, and we were curious about who is most likely to be portrayed in conjunction with each risk factor. We wanted analyze each of these dimensions across our articles.

To conduct this analysis, we constructed a comprehensive prompt to run with GPT-4o (See GPT prompt for qualitative analysis S1.3 directly above in the appendix), and ran a random sample of 110 articles (5 per year) from each risk on this prompt. While this is currently a non-standard approach to content analysis, we believe that the capabilities of this large language model are demonstrable and impressive. Across a broad range of tasks, GPT can outperform humans and on relatively basic coding tasks, such as those presented here, its output is likely to rival or even exceed that of typical research assistance. Many studies attest to GPT's performance at this type of task (e.g., Achiam et al., 2023; Bubeck et al., 2023; Sen et al., 2023; Zhang et al., 2023), and manual review of a small portion of the output confirmed its quality. As such, we take the output of GPT at face value and present the results across risks below.

Overall, we found that the majority of the analyzed articles ($N = 1,540$) only mentioned the risk in passing ($N = 1,234$; GPT rated discussion of risk as "Not relevant" or "Hardly at all"). Roughly 9.5% of the articles ($N = 146$, GPT rated as "Slightly") dedicated a modest portion of the text to discussion of the risk, and another 10.4% ($N = 160$) were "Mostly" or "Entirely" about the associated risk factor. In Figure S4, we present this categorization of articles for each of the risks. As this shows, relevance varies significantly across risk factors. Where most of the articles that mention overdosing and sexually transmitted diseases spend very little time discussing those risk factors, the articles that mention terrorism and homicide dedicate a much larger portion of the text to those risks.

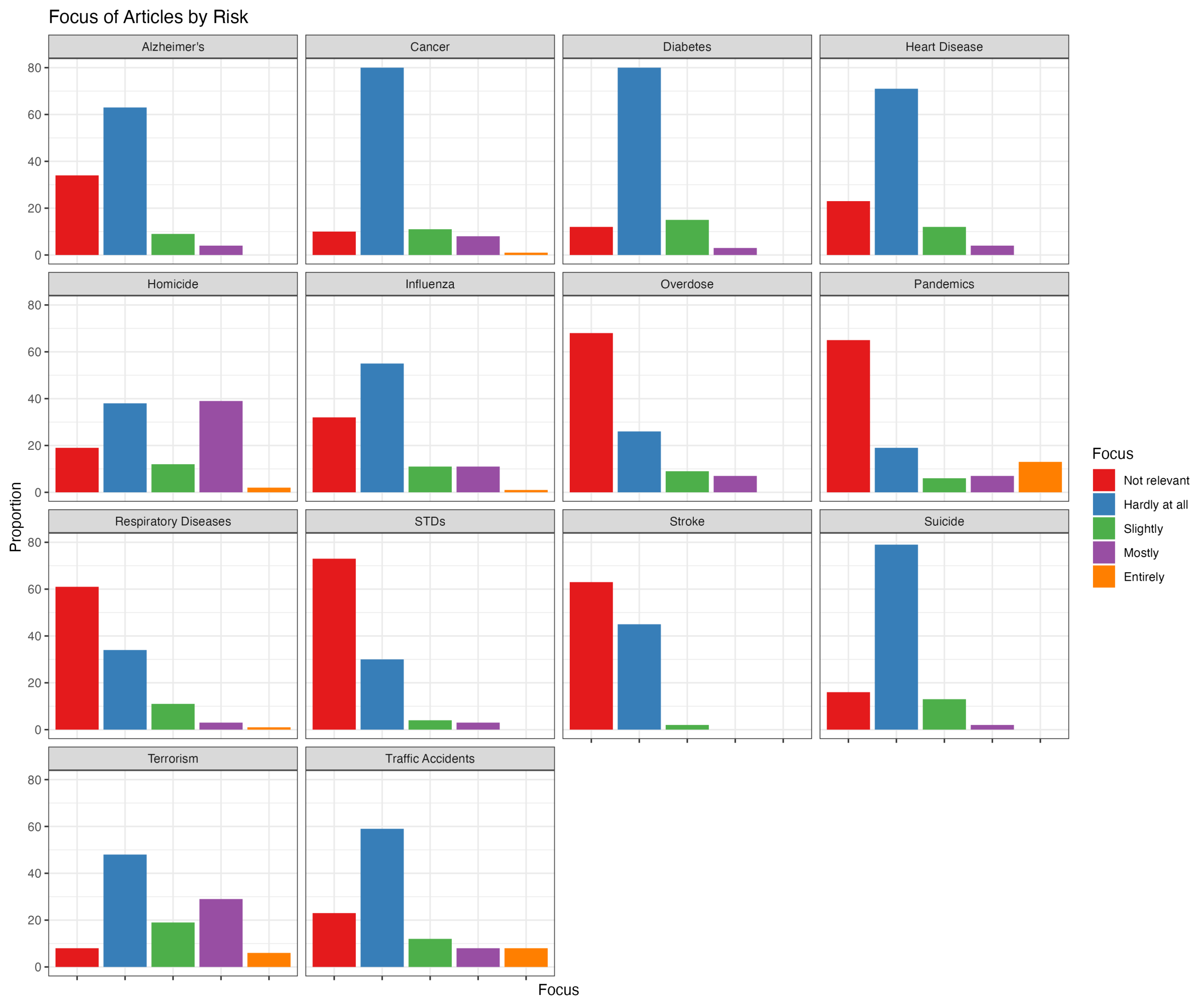

Figure S4: Counts of articles categorized by how focused the text was on the associated risk.

Next, we explore how much the articles discussed the causes of each of the risks, and what causes they most often pointed to. Given that many of our articles only mentioned the risks in passing it is perhaps not surprising that the majority of them (85.3%, $N = 1314$) did not discuss causes at all. Looking at the articles that did discuss the causes, we again find substantial variation across risks (Figure S5). For example, when articles discussed the causes of chronic respiratory disease (CRD), the causes were almost always presented as environmental. In contrast, diabetes was almost always described as driven by lifestyle choices, and overdose was split between these. Across risks, genetic causes ($N = 23$) were not mentioned nearly as much as environmental ($N = 127$) or lifestyle causes ($N = 126$, $p < 0.001$; Chi-Square test of independence).

Figure S5: Counts of articles that mention different causes in their discussion of each risk.

We now turn to discussion of risk mitigation strategies. As with the causes, the majority of articles ($N = 1130$, 73.4%) did not discuss methods to mitigate risk factors. When they did, articles discussed a great variety of mitigation strategies that fit into three major categories: behavioral – diet, exercise, and other behaviors; policies – communityoriented, education, and policy solutions; and technological – innovations/technologies, medical procedures, and other medications. Across risks, the articles tended to focus on technological ($N = 217$) and policy solutions ($N = 206$), over behavioral ones ($N = 117$, $p < 0.001$, Chi-Square test of independence). Again, these varied substantially across risks. For example, when articles about heart disease or diabetes discussed mitigation strategies, they focused on behavioral and technological (medical) solutions. In contrast, articles about homicide and terrorism almost exclusively discussed policy solutions, though they occasionally discussed new technologies that could help prevent these. See Figure S6 for a breakdown of the mitigation strategies discussed for each risk.

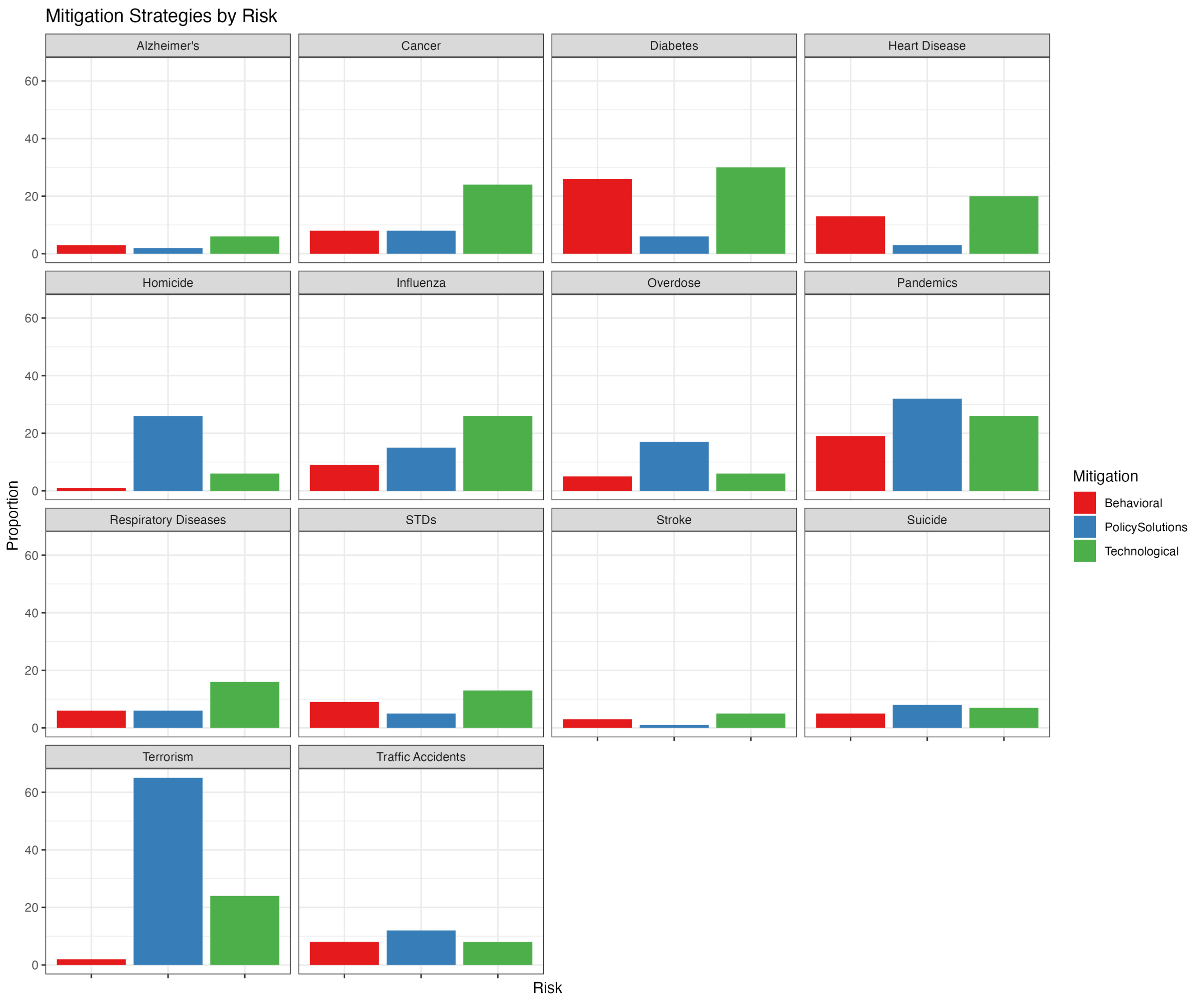

Figure S6: Counts of articles that mention different risk mitigation strategies in their discussion of each risk.

When articles discussed the causes and mitigation strategies for each risk, they sometimes did so using different framings or tones. For example, sometimes their discussion made the cause seem largely controllable and the mitigation strategy highly effective; other times, they made these seem much less attainable. To understand how these descriptions varied on these two dimensions, GPT provided numeric scores from 0 to 100 for both of these factors. Higher numbers indicate relatively greater amounts of controllability and mitigation effectiveness. Looking at controllability, the articles generally received middle scores, though ratings varied quite a bit (Mean = 57, SD = 23). The scores were distributed unequally across risks ($p = 0.005$, Kruskal Wallis test on risks with 5 or more scores); for example, traffic accidents, STDs and heart disease were described as relatively more controllable, whereas terrorism, COVID, and chronic respiratory disease were described as less controllable. Similar patterns were observed for the framing of the mitigation strategies (Mean = 63, SD = 21). While there was certainly variation in how effective the articles described the mitigation strategies across risks, this variation only approached significance ($p = 0.067$, Kruskal Wallis test on risks with 5 or more scores). We do not believe that this suggests that there is no variation here, but rather that our sample was too small and our measurement too crude to observe it given that many of the risks received similar scores. For this reason, we still present a plot of the means and SEs for mitigation effectiveness for each of these risks (Figure S7). This figure reveals how Alzheimer's and suicide are generally discussed as less effectively mitigated, whereas flu and stroke are more effectively mitigated. This likely has to do with the known behavioral preventions for the latter two and the lack of these for the former pair.

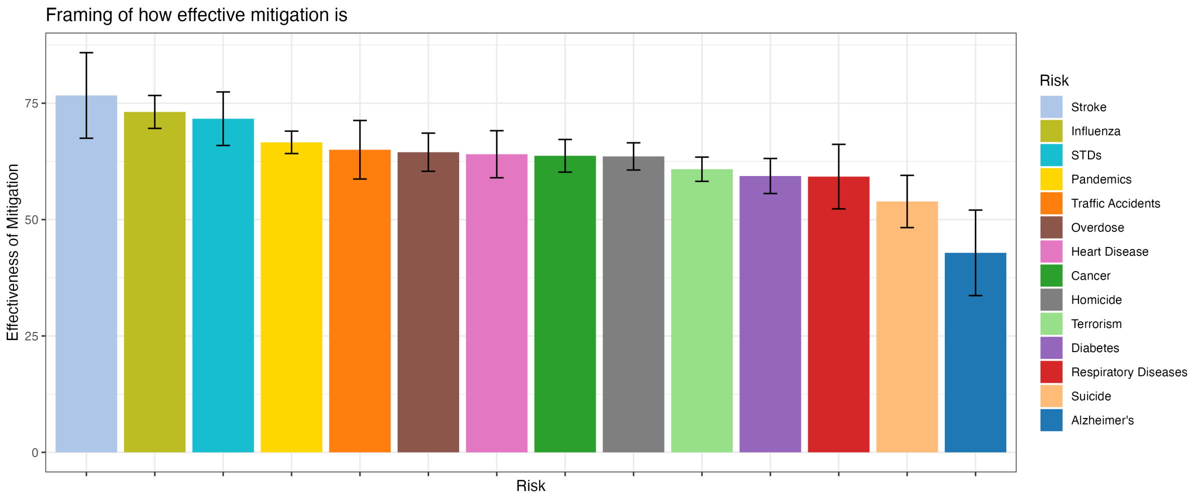

Figure S7: Means and SEs of how effective mitigation strategies are described as for different risks with higher numbers indicating a greater ability to mitigate

The articles also differed in their focus on the individual compared to the collective. For example, some articles discussed how risks affect broad populations using statistics, whereas others presented stories of individuals and their experience with a risk. Some articles described solutions that isolated people can implement, and others focused on more collective solutions. To understand the article's focus on the individual versus the collective, we had GPT score the solution strategy on a numeric scale from 0 (entirely individually focused) to 100 (entirely collective focus). We also had GPT rate the narrative in general using one of five options (Only collective, Mostly collective, Both, Mostly individual, Only individual). Looking at the solution strategies, we find that articles were a bit more likely to focus on collective than individual solutions across risks, but the variation was quite large (M = 61, SD = 32). These values were not equally distributed across risks ($p < 0.001$, Kruskal Wallis test on risks with 5 or more scores, Figure S8). For example, solutions to prevent terrorism and homicide were much more likely to be collectively focused whereas those for diabetes and heart disease were more likely to focus on the individual. Similar findings were found for the narrative focus ($p < 0.001$, Kruskal Wallis test on risks with 5 or more scores) with a few key differences. For example, while terrorism was generally presented from a collective perspective, homicide became much more (relatively) individual focused, likely due to the fact that much of the coverage focused on specific instances of homicide. In contrast, diabetes became relatively more collective focused, likely because the coverage often described population-level information about this disease. See Figure 3 from the main text for depiction of how all risks faired on this measure.

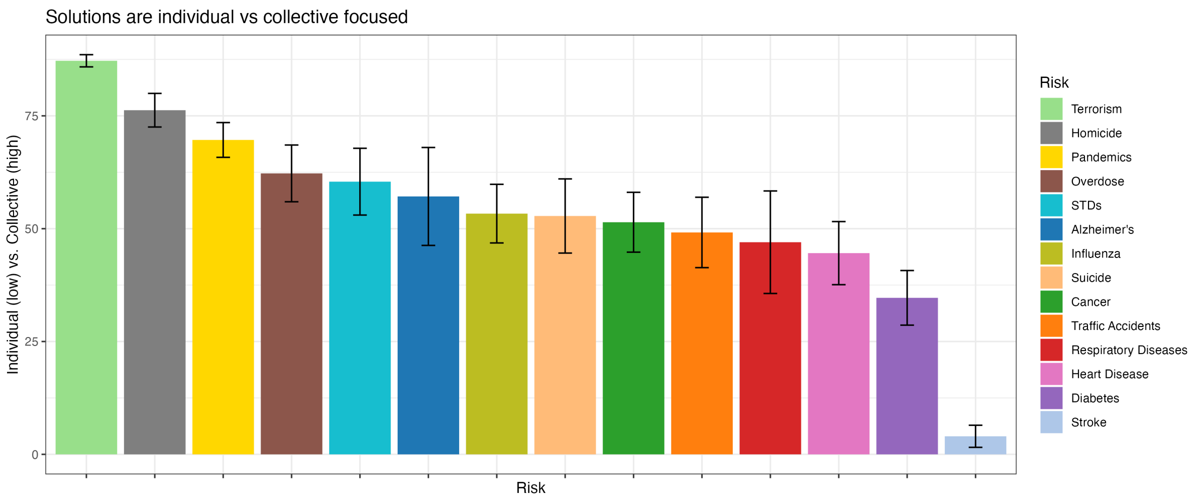

Figure S8: Means and SEs of whether solution strategies for preventing a risk focused on the collective (high numbers) or the individual (low numbers).

When it comes to understanding text, sentiment analysis—understanding how positive or negative a message is—is a commonly used method that has provided numerous insights. We employed this methodology by having GPT score the sentiment of each text (on a scale from -10, very negative, to 10, very positive), and we also had it rate how threatening the risk was described as (0: not at all threatening, to 10: very threatening). In general, the texts leaned negative in sentiment, though there was considerable variation across articles (Mean = -1.9, SD = 3.6). This variation was unequally distributed across risks ($p < 0.001$, Kruskal-Wallis test) with the more sensational risks (e.g., homicide and terrorism) receiving the most negative ratings whereas illnesses like heart disease, diabetes, and STDs were described in a largely neutral manner (See Figure 3, Panel B main text). Similar results were found for the threat scores. While most articles were scored as only slightly threatening, there was considerable variation across all risks (Mean = 3.5, SD = 3.0, $p < 0.001$ Kruskal-Wallis test). The more sensational risks were depicted as more threatening, and the chronic illnesses were depicted as much less threatening.

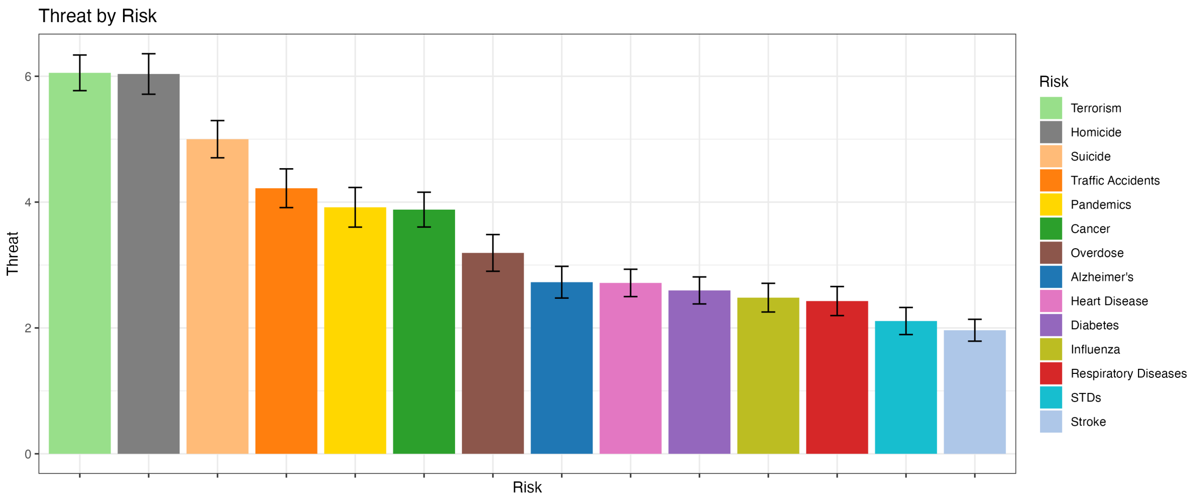

Figure S9: Means and SEs of how threatening each risk is described as.

Finally, we describe the demographics that were discussed in articles about each of the risks. We tasked GPT with identifying any demographics that were present in each article. In the 1540 articles, GPT identified 692 mentioned demographics relevant to descriptions of risks. These fell into a number of categories including race ($N = 92$), gender ($N = 156$), age ($N = 230$), SES ($N = 135$), sexual orientation ($N = 5$), geographic region ($N = 13$), occupation ($N = 5$), religion ($N = 1$), pre-existing health condition ($N = 54$), and legal status ($N = 1$). Because many of these were mentioned only a few times, we limit the remaining analysis to race, gender, age, and SES which all had more than 90 mentions. Note that these are still very small N's, so while we highlight some of the difference by risk and category, these should be viewed as preliminary results.

While it was still rarely mentioned, race was much more likely to be mentioned in articles about homicide ($N = 18$), terrorism ($N = 12$), suicide ($N = 10$), and pandemics/COVID-19 ($N = 10$). African American was the most commonly mentioned race (29) followed by white (14). When it came to gender, the majority of articles that discussed specific genders described males ($N = 110$), with only 61 focusing on females and only one on transgender individuals. Gender was mentioned most often in articles about homicide ($N = 30$), traffic accident ($N = 20$), suicide ($N = 17$), and cancer ($N = 15$). Age was more commonly mentioned across all risk factors, though it was most common in articles on homicide ($N = 28$), traffic accidents ($N = 29$), suicide ($N = 20$), and diabetes ($N = 20$). Across all risks, children received relatively few mentions ($N = 33$), followed by the elderly ($N = 57$), young adults ($N = 97$), and finally adults in general ($N = 113$). Finally, SES was again most commonly mentioned for homicide ($N = 20$), followed by pandemics/COVID-19 ($N = 19$), overdose ($N = 15$), and diabetes ($N = 15$). When SES was mentioned, it tended to be in regard to lower income individuals. In general this demographic analysis illustrates that the news is more likely to focus on certain demographic groups than others but that this too changes from risk to risk.

S1.5 Supplemental analysis with sentiment analysis using VADER.

Our qualitative analysis was conducted on a small sample of the whole number of articles. To assess how general the insights derived from this analysis were for the complete dataset, we wanted to run an additional analysis on all the articles. Due to cost-constraints with GPT-4 we needed to use a different approach. Given the ubiquity of sentiment analysis in natural language processing research and the manner in which sentiment distinguished our sensational from chronic risks, we analyzed the sentiment of all articles in the dataset as a first comparison.

To calculate an article's sentiment, we used the Valence Aware Dictionary and sEntiment Reasoner (VADER, Gilbert & Hutto, 2014), which uses dictionary words and simple heuristics to code the valence of short texts. VADER has been shown to outperform many commonly used sentiment analysis tools (Ribeiro et al., 2016) and has been used for a diversity of tasks including to study emotions (Fan et al., 2019; Bathina et al., 2021), to evaluate US patient experience with health care (Sewalk et al., 2018), and to assess public attitudes during the COVID-19 pandemic (Valdez et al., 2020). To score our articles, we broke every text into sentences with the NLTK package in python (Hardeniya et al., 2016), calculated the compound VADER score for each sentence, and averaged them at the article level to arrive at a single measure of sentiment. These ratings were moderately well correlated with the ratings GPT provided at the article level ($r = 0.38$, $p < 0.001$), which meant that averaging across articles for each risk produced a very strong correlation ($R = 0.91$, $p < 0.001$). We then calculated the mean sentiment for each risk for every month in our dataset and across the entire interval. Figure S10 displays the average sentiment for each risk factor.

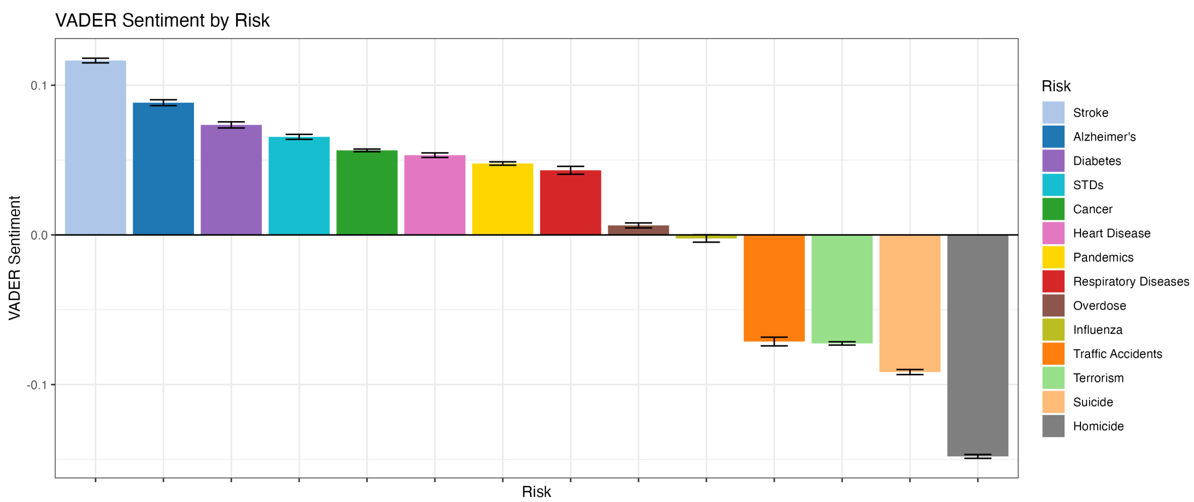

Figure S10: Means and 95% confidence intervals of VADER sentiment for each risk across all articles.

We also plot the time series showing mean monthly sentiment for every risk over the entire interval in Figure S11. Note that COVID-19 included mentions of "pandemic" and "epidemic" which explains why there were mentions of this risk from before 2019. This plot makes clear that different risks experienced very different trends over this period. For example, homicide became less negative over time, whereas articles about the flu seemed to have stable sentiment though large variability across the interval. Finally, traffic had a large decline in sentiment after 2008 which may imply that articles that cover traffic accidents may have been influenced by the financial crisis of 2008-09.

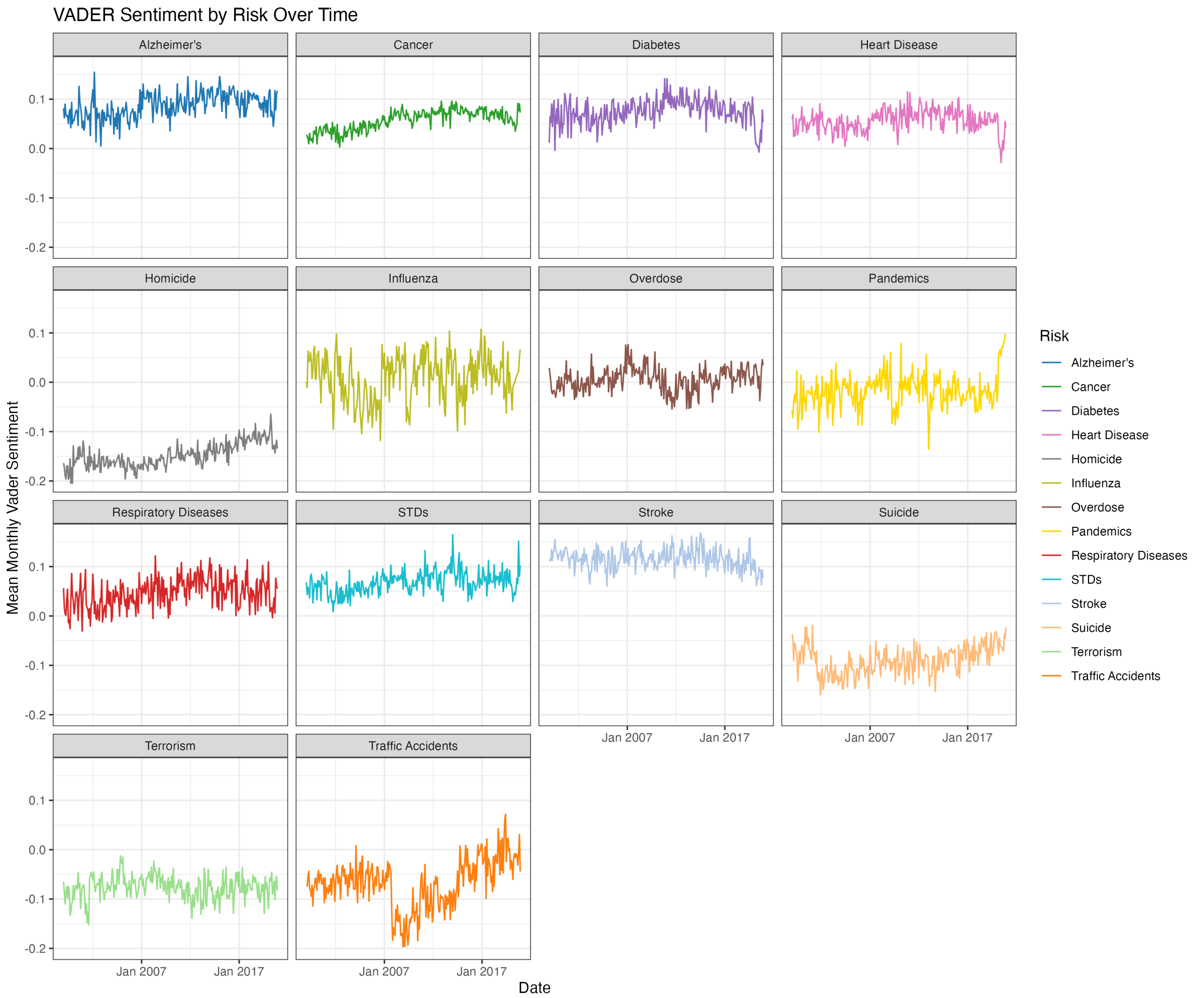

Figure S11: Means monthly VADER sentiment for each risk from 1999 to 2020

S1.6 Divergences from the Pre-registration

We pre-registered this study here: https://doi.org/10.17605/OSF.IO/MR2AY. As we conducted the analysis, we realized that there were a few instances where modifications were necessary. We detail these modifications below.

1) In the regressions with the leveled data, we included a monthly dummy variable to ensure that any results were not merely a product of seasonality. We forgot to declare that we would include this control variable in our pre-registration, though we believe its inclusion is most appropriate for the model.

2) In the part of our preregistration on the GPT qualitative analysis, we incorrectly stated that 5 articles every year would add up to 105. In truth this adds up to 110 because there are 22 years included between 1999-2020. This was a simple arithmetic error that we corrected in the main text.

3) The sentiment analysis with VADER was not pre-registered. We decided to include this analysis to shed light on whether the qualitative observations we made on the small-scale data were prevalent throughout the entire period relevant for this study. This was the only addition, and there are no file-drawer measurement strategies.

S1.7 Supplemental References

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