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The perception of dramatic risks: Biased media, but unbiased minds

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ABSTRACT

In their famous study on risk judgments, Lichtenstein, Slovic, Fischhoff, Layman, and Combs (1978) concluded that people tend to overestimate the frequencies of dramatic causes of death (e.g., homicide, tornado) and underestimate the frequencies of nondramatic ones (e.g., diabetes, heart disease). Further, their analyses of newspapers indicated that dramatic risks are overrepresented in the media—suggesting that people's distorted risk perceptions might be driven by distortions in media coverage. Although these patterns were not evaluated statistically in the original analyses, the conclusions have become a staple in the social sciences. How reliable are they? And are they replicable? In a systematic literature search, I identified existing replications of Lichtenstein et al.'s investigation and submitted both the original data and the data from the replications to a Bayesian statistical analysis. All datasets indicated very strong evidence for an overrepresentation of dramatic risks and an underrepresentation of nondramatic risks in media coverage. However, a reliable overestimation (underestimation) of dramatic (nondramatic) risks in people's frequency judgments emerged only in Lichtenstein et al.'s dataset; it did not replicate in the other datasets. In fact, aggregated across all datasets, there was evidence for the absence of a differential distortion of dramatic and nondramatic causes of death in people's risk frequency judgments. Additional analyses suggest that when judging risk frequency, people rely on samples from their personal social networks rather than from the media. The results reveal a limited empirical basis for the common notion that distortions in people's risk judgments echo distortions in media coverage. They also suggest that processes of risk frequency judgments include a metacognitive mechanism that is sensitive to the source of mentally available samples.

1. Introduction

How well are people calibrated to the frequency of harmful events in the environment? In their seminal investigation of people's judgments of health risks, Lichtenstein et al. (1978) asked respondents to assess the annual mortality rate in the United States for 41 causes of death, including diseases, accidents, and natural hazards. For some causes of death the judged frequencies deviated considerably from the objective ones. Moreover, the deviations seemed to follow a particular pattern: The authors found support for their hypothesis "that the frequencies of dramatic events such as cancer, homicide, or multiple-death catastrophes … would be overestimated, while the frequencies of 'quiet killers' would be underestimated" (p. 552). Lichtenstein et al. also proposed "the unrepresentative coverage of these causes of death in the news media" (p. 575) as a possible reason for people's distorted judgments of dramatic risks. In analyses of newspaper reports, they found that media coverage distorted the relative prevalence of dramatic causes of death in terms of both the frequency with which they were mentioned and how many square inches were devoted to them (see also Combs & Slovic, 1979). Regression analyses suggested an association between media coverage and people's frequency judgments.

The conclusions in Lichtenstein et al. (1978) have become a staple in the social and behavioral sciences. Viscusi (1998) summarized the literature as follows: "dramatic risks … tend to be overestimated" (p. 22), and Rosen (2004) stated that "people overestimate the frequency of death from dramatic disasters such as tornados, floods, fire, and homicide and underestimate the frequency of deaths from diabetes, stomach cancer, stroke, and asthma" (p. 76; see also Newell, Lagnado, & Shanks, 2022). The notion of a link between distorted risk judgments and unrepresentative media coverage can be found in scholarly articles (e.g., Alba, Chromiak, Hasher, & Attig, 1980; Brown & Siegler, 1993; Frost, Frank, & Maibach, 1997; Kellermann, 1985), textbooks (e.g., Breakwell, 2014), and popular belief. Gardner (2008) summed the idea up neatly: "one of the most consistent findings of risk perception research is that we overestimate the likelihood of being killed by the things that make the evening news and underestimate those that don't" (p. 67). And in the

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words of Wucker (2021): "People over-weighted the events that cause the greatest emotional impact … because they get a lot of attention in the media" (p. 149). Finally, also for Kahneman (2011), "[t]he lesson is clear: estimates of causes of death are warped by media coverage" (p. 138).

Lichtenstein et al.'s (1978) conclusions that people's risk judgments echo distortions in media coverage have often been cited to illustrate the availability heuristic (e.g., Baron, 2023; Folkes, 1988; Hardman, 2009; Johnson & Tversky, 1983; Kahneman, 2011; Morgan et al., 1983). According to this heuristic, people judge the frequency or probability of an event based on the ease with which instances or occurrences of the event come to mind (Tversky & Kahneman, 1973). To the extent that "differential media portrayal makes some types of deaths easier to recall than others (Lichtenstein et al., 1978), […] people erroneously believe that homicide occurs more than suicide and that death occurs more from fire than from drowning" (Folkes, 1988, p. 13).

But how systematic and reliable are the findings that dramatic risks are overestimated by individuals and overrepresented in the media? First, it is important to note that Lichtenstein et al.'s (1978) conclusions regarding distortions of dramatic risks in people's risk judgments and media coverage were based on observational rather than formal analysis. Overestimation and underestimation were diagnosed based on whether the geometric mean (across participants) response for a cause of death lay above or below an estimated regression line representing the relationship between (log-transformed) estimated and actual frequencies of the risks. Using this approach, the authors concluded:

> among the most overestimated causes of death (relative to the regression line) were botulism, tornado, flood, homicide, motor vehicle accidents, all accidents, and cancer. These are all sensational events. Most of the causes of death that were underestimated (relative to the regression line)—asthma, tuberculosis, diabetes, stomach cancer, stroke, and heart disease—seem to be undramatic, quiet killers. (p. 575)

These observations, however, were not backed up by a statistical test to establish whether dramatic and nondramatic risks indeed differed reliably in how they were distorted in people's frequency judgments.

The distortions of dramatic and nondramatic risks in media coverage were characterized by Lichtenstein et al. (1978) as follows:

> 19 of the listed causes of death were never mentioned. Some of these 19 causes are quite frequent: cancer of the digestive system, diabetes, breast cancer, and tuberculosis. In contrast, the eighth most frequently reported cause of death in the newspapers, tornadoes, is in fact relatively rare. … Note also that homicide, which is 23% *less* frequent than suicide, was reported 9.6 times as often, with 15 times as much space devoted to it. (p. 569)

But again, no statistical test was conducted to test for a difference between distortions of dramatic and nondramatic events.

A second caveat to the notion of a media-induced distortion in people's judgments of dramatic and nondramatic risks is that the evidence cited in the literature in support of this notion derives more or less exclusively from the analysis by Lichtenstein et al. (1978). Do the patterns highlighted in that study—if they hold up to a statistical evaluation—replicate?

The goal of this article is to test the reliability and replicability of the notions that in the media dramatic risks—as characterized by Lichtenstein et al. (1978) and the companion article by Combs and Slovic (1979)—are disproportionally distorted relative to their actual prevalence and that this distortion is paralleled by a similar distortion in people's frequency judgments. To that end, I conducted a systematic literature search to locate replications of Lichtenstein et al.'s investigation, then submitted their original data as well as the replication datasets to a statistical evaluation. I also synthesized all datasets to estimate an overall effect. In the statistical analyses, I relied on a Bayesian framework, which makes it possible to also quantify the amount of evidence for the absence of an effect.

Whether Lichtenstein et al.'s (1978) findings are robust could have substantial implications for theories of cognition. A consistent parallel between distortions in media coverage and distortions in risk judgments would suggest that people rely on any instance that is mentally available to them, irrespective of the origin and validity of the information. This would support the notion that people are metacognitively myopic with regard to the content of their mental samples (e.g., Fiedler, 2000; Fiedler, Prager, & McCaughey, 2023). By contrast, if evidence for a parallel between distortions in media coverage and risk judgments does not emerge consistently, this would suggest that people take the source of mentally available occurrences of events into account when making frequency judgments (cf. Oppenheimer, 2004). It would underscore that models of how people process mentally available instances for judgments of frequency and probability also require a metacognitive mechanism that relies on available samples of information depending on their validity for the given judgment task.

2. Methods

All data, materials, and analysis code are available at https://osf.io/u4d7g.

2.1. Literature search

To identify datasets that collected risk frequency judgments and measures of media coverage for the set of causes of death used in Lichtenstein et al. (1978), I employed ISI Web of Science and searched all articles that had cited Lichtenstein et al. as of April 2023. In addition, I asked all recipients of the mailing list of the Society of Judgment and Decision Making for published and unpublished datasets that represent replications of Lichtenstein et al.'s analysis. To be considered for inclusion the set of causes of death investigated needed to cover at least 20 (i.e., half) of the 41 causes of death studied by Lichtenstein et al. Further, to be able to directly compare distortions in risk frequency judgments and distortions in media coverage, I focused on datasets in which both measures were collected.

The search produced a total of 816 articles. I screened the abstracts of all of these articles; if there were indications in the abstract that risk frequency judgments or measures of media coverage for causes of death had been collected, I checked the article for further methodological details. In the end, there were two articles that collected both risk frequency judgments and measures of media coverage for the causes of death investigated in Lichtenstein et al.'s (1978) study (Hertwig, Pachur, & Kurzenhäuser, 2005; Pachur, Hertwig, & Steinmann, 2012). The search also yielded five articles, encompassing a total of eight datasets, that collected frequency judgments only (Armantier, 2006; Benjamin, Dougan, & Buschena, 2001; Hakes & Viscusi, 2004; LaCour & Davis, 2020; Morgan et al., 1983). Four additional articles were not included in the analysis because they used fewer than half of Lichtenstein et al.'s causes of death (Harrison & Rutström, 2006; Johnson & Tversky, 1983; Wright, Bolger, & Rowe, 2002; Yamagishi, 1994) and one article was not included because it was based on judgments of personal risk (Greening & Dollinger, 1992). Although in the main analyses below I focus on the datasets that collected both risk frequency judgments and measures of media coverage—that is, Lichtenstein et al., Hertwig et al., and Pachur et al.— I report the results when including all datasets that collected risk frequency judgments (even those that did not collect measures of media coverage) in Appendix C.

2.2. Materials

2.2.1. Risks

The set of causes of death in Lichtenstein et al.'s (1978) investigation consisted of 41 events "chosen to represent the range of frequencies of causes of death for which yearly statistics are available. Obscure or unfamiliar causes were excluded, as were causes showing large fluctuations from year to year" (p. 554). I categorized the risks as dramatic or nondramatic based on relevant statements in Lichtenstein et al. and Combs and Slovic (1979). Although the authors did not provide a definition of "dramatic risks," they presented several examples of events that they considered to fall into this category; in addition, they characterized dramatic risks as those that were "sensational," "violent," or "often catastrophic" (e.g., Lichtenstein et al., p. 568 and p. 575); nondramatic risks, by contrast, were described as "quiet" and "common but usually non-fatal" (e.g., Lichtenstein et al., p. 568 and p. 572). A detailed description of the categorization procedure and the specific statements in Lichtenstein et al. and Combs and Slovic that I used for the categorization is provided in Table A1 in Appendix A. Overall, 22 of the 41 causes of death were categorized as dramatic and 17 were categorized as nondramatic. Lacking relevant statements, two causes of death (suicide and "pregnancy, abortion, and childbirth") remained uncategorized and were therefore not included in the analyses that relied on the categorizations (they were included, however, in the analyses using the continuous drama intensity ratings, mentioned shortly). For a list of all 41 risks and their categorization, see Table 1. To have an additional and independent measure of how dramatic the causes of death are, I asked $N = 250$ participants to rate how dramatic they found each of the 41 causes of death on a 9-point scale (details of the study are reported in Appendix B). In brief, the mean (across participants) continuous ratings for each cause of death—shown in Fig. 1—strongly converged with the categorizations derived from the statements in Lichtenstein et al. and Combs and Slovic, point-biserial correlation $r = 0.70$ ($BF_{10} = 24{,}004$).

2.2.2. Risk judgments

In all three datasets (i.e., Hertwig et al., 2005; Lichtenstein et al., 1978; Pachur et al., 2012), frequency judgments for the causes of death were elicited by asking participants to estimate the total number of deaths due to each risk per year in the population (the datasets used were Experiment 3 in Lichtenstein et al., 1978; the assorted set in Study 1 in Hertwig et al., 2005; and Study 2 in Pachur et al., 2012). In Lichtenstein et al., the judgments referred to the United States, in Hertwig et al. to Germany, and in Pachur et al. to Switzerland. As the judged frequency of each risk, I used the aggregate (median or geometric mean) responses across all participants in each study. For the Lichtenstein et al. data, I used an average—weighted by sample size—of the aggregate estimates obtained in two separate conditions, in which different standard values were provided to participants. The number of participants in the three datasets were $N = 74$ (Lichtenstein et al.), $N = 45$ (Hertwig et al.), and $N = 85$ (Pachur et al.).

Table 1
Causes of death investigated by Lichtenstein et al. (1978) listed by category in the current analysis.

Dramatic events	Nondramatic events	Noncategorized events
All accidents[6,7]	Accidental falls[2]	Pregnancy, abortion, and childbirth
All cancer[1,6]	All disease[7]	Suicide
Botulism[6]	Appendicitis[7]	
Breast cancer[1]	Asthma[3,5]	
Drowning[7]	Diabetes[5]	
Electrocution[6,8]	Emphysema[7]	
Excess cold[6,8]	Heart disease[5]	
Fire and flames[7]	Infectious hepatitis[7]	
Firearm accident[8]	Measles[7]	
Fireworks[6,8]	Polio[7]	
Flood[6,8]	Smallpox[7]	
Homicide[1,6]	Smallpox vaccination[3]	
Leukemia[1,2]	Stomach cancer[5]	
Lightning[8]	Stroke[5]	
Lung cancer[1]	Syphilis[7]	
Motor vehicle accident[6,7,8]	Tuberculosis[4,5]	
Motor–train collision[6,7,8]	Whooping cough[7]	
Nonvenomous animal[6,8]		
Poisoning by vitamins[4]		
Poisoning solid/liquid[4]		
Tornado[6,7,8]		
Venomous bite or sting[6,8]		

Note. Superscripts indicate the statement(s) in Lichtenstein et al. (1978) and Combs and Slovic (1979), reported in Table A1 in Appendix A, that were used as a basis to categorize each risk. In Hertwig et al. (2005) and Pachur et al. (2012), "stomach cancer" was presented as "cancer of the digestive system."

2.2.3. Media coverage

Several approaches to measuring media coverage for each risk were employed in the three datasets. Lichtenstein et al. (1978) considered three measures: Analyzing a local daily newspaper, the authors determined the total number of deaths reported for a year (*media frequency*) as well as the square inches of reporting devoted to the deaths, excluding photographs (*media inches*); they also asked participants to rate, on a scale of 1–5, how often they had heard about the risk as a cause of death in the media (*indirect experience*). A similar approach was used by Pachur et al. (2012), who asked participants to indicate, separately for each risk, the absolute number of instances of the causes of death that they could recall from information and entertainment media (i.e., newspapers, TV, radio, internet, movies, and novels). Hertwig et al. (2005) determined the number of times the terms denoting each cause of death were mentioned in German print media, using an extensive data archive of daily and weekly newspaper articles. The strategy seemed inappropriate for "firearm accident," "venomous bite or sting," "motor–train collision," and "all cancer" because they might be described more verbosely; therefore, no measures of media coverage were collected for these four causes of death in Hertwig et al.

2.2.4. Quantifying distortions in media coverage and people's frequency judgments

In order to assess the extent to which the distributions of the risks in media coverage and people's frequency judgments deviated from the risks' actual frequency distribution, I first determined, separately for each dataset, the *relative rank* of each cause of death on the measures of media coverage, frequency judgments, and actual frequencies. The relative rank is defined as $(r_i\text{-}1)/(N\text{-}1)$, where r_i is the rank (according to the respective measure) of risk i among a total of N risks. The relative rank expresses the proportion of other risks in the set that have a lower rank than risk i. Average rank was used for ties. This yielded a *media rank* (the relative rank according to the measure of media coverage), a *judgment rank* (the relative rank according to the frequency judgments), and an *actual rank* (the relative rank according to the actual frequencies in the respective country) for each risk. I relied on ranks rather than absolute values because all the variables had a skewed distribution, which can compromise the results of statistical tests. Another attractive feature of using relative ranks is that it puts all the variables on the same scale. To quantify the distortion in media coverage, I next calculated the difference between each risk's media rank and its actual rank. For the Lichtenstein et al. (1978) data, the analyses reported refer to the media rank derived from the approach of measuring media coverage in terms of indirect experience (see Section 2.2.3), but the same conclusions were obtained when using the other two approaches (i.e., media frequency and media inches; see Appendix D). To quantify the distortion in people's frequency judgments, I calculated the difference between each risk's judgment rank and its actual rank. Note that quantifying misrepresentations and misperceptions of the risks in terms of differences in relative ranks captures distortions in the ordering of the risks, which is a frequently discussed issue in risk perception research (e.g., Combs & Slovic, 1979; Slovic, 1987). Nevertheless, using ranks may be insensitive to more nuanced distortions in the representation of the risks; the current approach should therefore be considered a conservative measure of distortion.

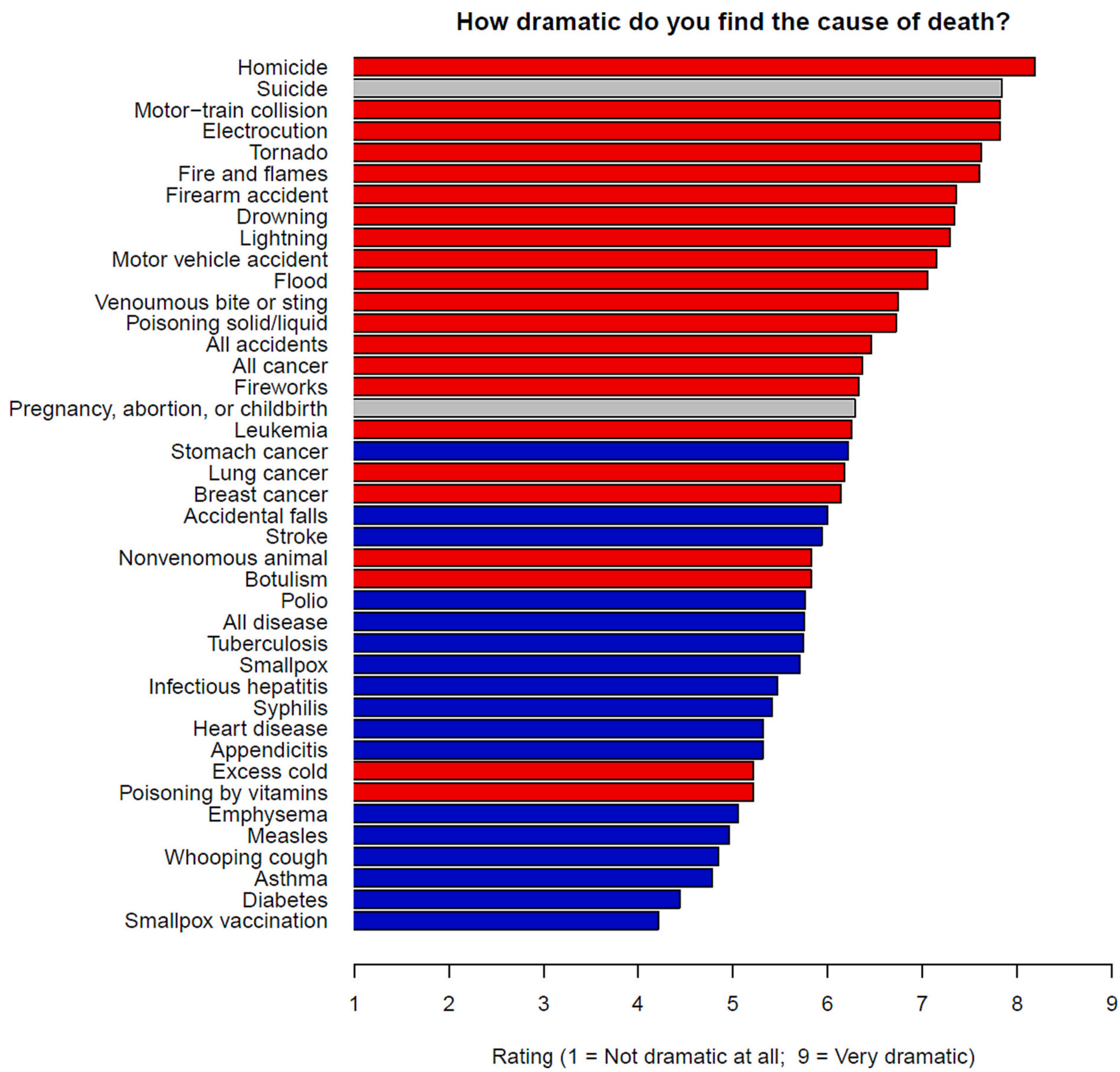

Fig. 1. Average drama intensity rating in the online study for each cause of death (see Appendix B for details). Red (blue) bars indicate causes of death categorized as dramatic (nondramatic) based on statements in Lichtenstein et al. (1978) and Combs and Slovic (1979)—see Table 1; grey bars indicate uncategorized causes of death. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Results

Fig. 2 plots, separately for each of the three datasets, each risk's actual rank against its media rank (upper panels) and judgment rank (lower panels), with circle markers denoting dramatic risks and triangle markers denoting nondramatic risks. Markers on the diagonal indicate that the risk's media rank (judgment rank) corresponds to its actual rank. Markers above the diagonal indicate a relative overrepresentation (overestimation) of the risk in media coverage (judged frequency), and markers below the diagonal indicate a relative underrepresentation (underestimation).

There seems to be a marked difference in media coverage between dramatic and nondramatic risks in all three datasets: Dramatic risks are primarily above the diagonal and nondramatic risks are primarily below the diagonal. This suggests that the media typically overrepresents dramatic risks relative to their actual frequencies and underrepresents nondramatic risks. A difference between dramatic and nondramatic risks in people's frequency judgments is less clear. There is a trend of dramatic risks lying above and nondramatic risks lying below the diagonal for the Lichtenstein et al. (1978) data, but this pattern seems to be less pronounced in Hertwig et al.'s (2005) and Pachur et al.'s (2012) datasets.

The differences between the distortions in dramatic and nondramatic risks were evaluated statistically using a Bayesian regression approach (with the R package *brms*; Bürkner, 2017). For media coverage (frequency judgments), the analyses included as dependent variable the difference between a risk's media rank (judgment rank) and its actual rank. To estimate the effect of how dramatic a cause of death is, the regression model included either (a) the categorization of whether the risk was a dramatic or a nondramatic event (the "category" factor; see Table 1) or (b) the continuous drama intensity ratings as predictor (the "ratings" factor; see Fig. 1). To control for the possibility that dramatic and nondramatic risks differ systematically in how frequently they occur (which might produce a spurious correlation between how dramatic a risk is and its value on the respective dependent variable), actual rank was included as covariate. The amount of evidence for differences between dramatic and nondramatic events was evaluated using Bayes factors (BF)—determined using the bayes_factor() function. The BFs were derived from comparing the regression model that included category as a predictor to a model that did not (an analogous approach was

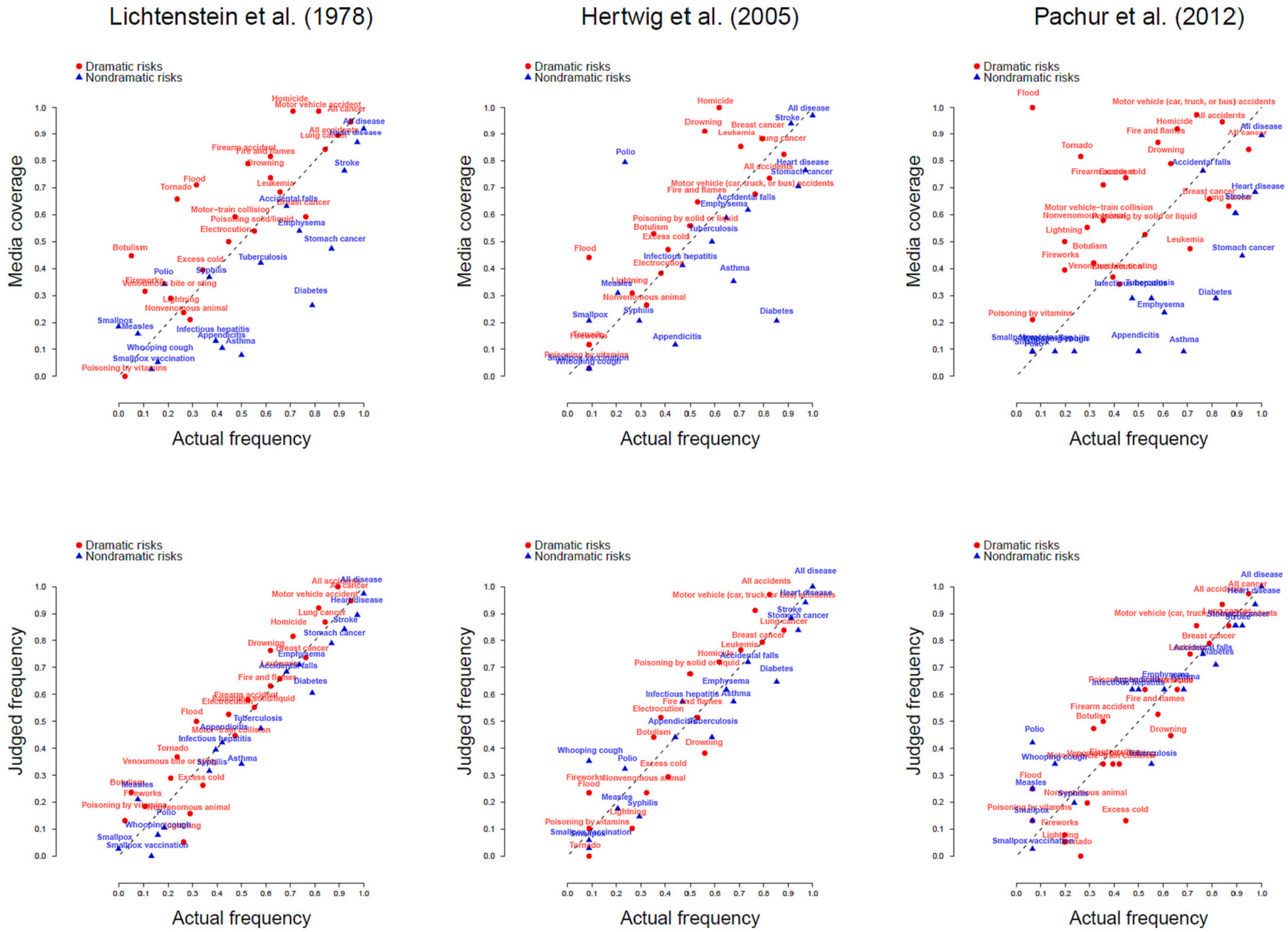

Fig. 2. Media rank (according to measures of media coverage; upper panels) and judgment rank (according to people's frequency judgments; lower panels) of the causes of death investigated by Lichtenstein et al. (1978) plotted against their actual ranks.

used when determining BFs for other predictors). A BF_{10} of 1–3 indicates weak (i.e., inconclusive) evidence for an effect. A BF_{10} of 3–10, 10–30, or < 30 indicates moderate, strong, or very strong evidence, respectively; conversely, a BF_{10} of 1/3–1, 1/10–1/3, 1/30–1/10, or $< 1/30$ indicates weak (i.e., inconclusive), moderate, strong, or very strong evidence for the *absence* of an effect, respectively (cf. van Doorn et al., 2021; Wagenmakers, Love, et al., 2018).[1] Finally, to summarize across all three datasets, I ran mixed-effects regression models, predicting the respective deviation from the actual rank for each risk in each of the datasets, with either category (dramatic vs. nondramatic event) or the continuous drama intensity ratings as fixed effect and random intercepts for the different causes of death. As recommended by Lin, Tong, Chen, & Wang (2020), no random effects were estimated for the dataset because the estimation of random effects is unstable for a factor with only three (as there are three datasets) levels (see also Borenstein, Hedges, Higgins, & Rothstein, 2010).

The results of the regression analyses are shown in Figs. 3 and 4. Let us first turn to the models predicting the risks' distortion in media coverage (Figs. 3A and 4A). For all three datasets, there is a credible effect of category (indicated by the 95% highest density intervals of the regression coefficients not including zero)—that is, dramatic and nondramatic events differ in how their relative frequencies are distorted in media coverage. The same also holds when using the continuous drama intensity ratings as predictor. The effects are consistently positive, meaning that compared to their actual relative frequencies, more dramatic risks tend to be overrepresented and less dramatic risks tend to be underrepresented in the media. The evidence for the effects is very strong for the datasets in Lichtenstein et al. (1978; category: $BF_{10} = 747.496$; ratings: $BF_{10} = 28{,}119.625$) and Pachur et al. (2012; category: $BF_{10} = 15{,}940.640$; ratings: $BF_{10} = 19{,}907.059$), as well as for the dataset in Hertwig et al. (2005) when using the continuous ratings as predictor ($BF_{10} = 62.237$). For the latter dataset, the evidence was weak when using category as predictor ($BF_{10} = 1.874$). In the mixed-effects regression models that estimated the overall effects across the datasets, the effects for category and ratings were $b = 0.256$ ($HDI_{95\%} = [0.154, 0.358]$), and $b = 0.145$ ($HDI_{95\%} = [0.101, 0.187]$), respectively. For both effects, the evidence was very strong (category: $BF_{10} = 2430.486$; ratings: $BF_{10} = 210{,}914.298$). Overall, the analyses consistently support the notion that dramatic and nondramatic events differ in how they are distorted in media coverage—despite the substantial changes in the media ecology that have occurred between the Lichtenstein et al. study and the two more recent ones. As an aside, note that

[1] BFs rather than frequentist p values were used for statistical inference in particular because nonsignificant p values are noninformative with regard to whether there is evidence in favor of the null hypothesis (i.e., evidence for the absence of an effect) or evidence that favors neither the null hypothesis nor the alternative hypothesis (i.e., inconclusive evidence; Wagenmakers, Marsman et al., 2018). This limitation is particularly relevant in the present case, as some of the reported effects provide evidence for the absence of a difference between dramatic and nondramatic causes of death. Drawing conclusions regarding an absence of a difference is impossible based on p values.

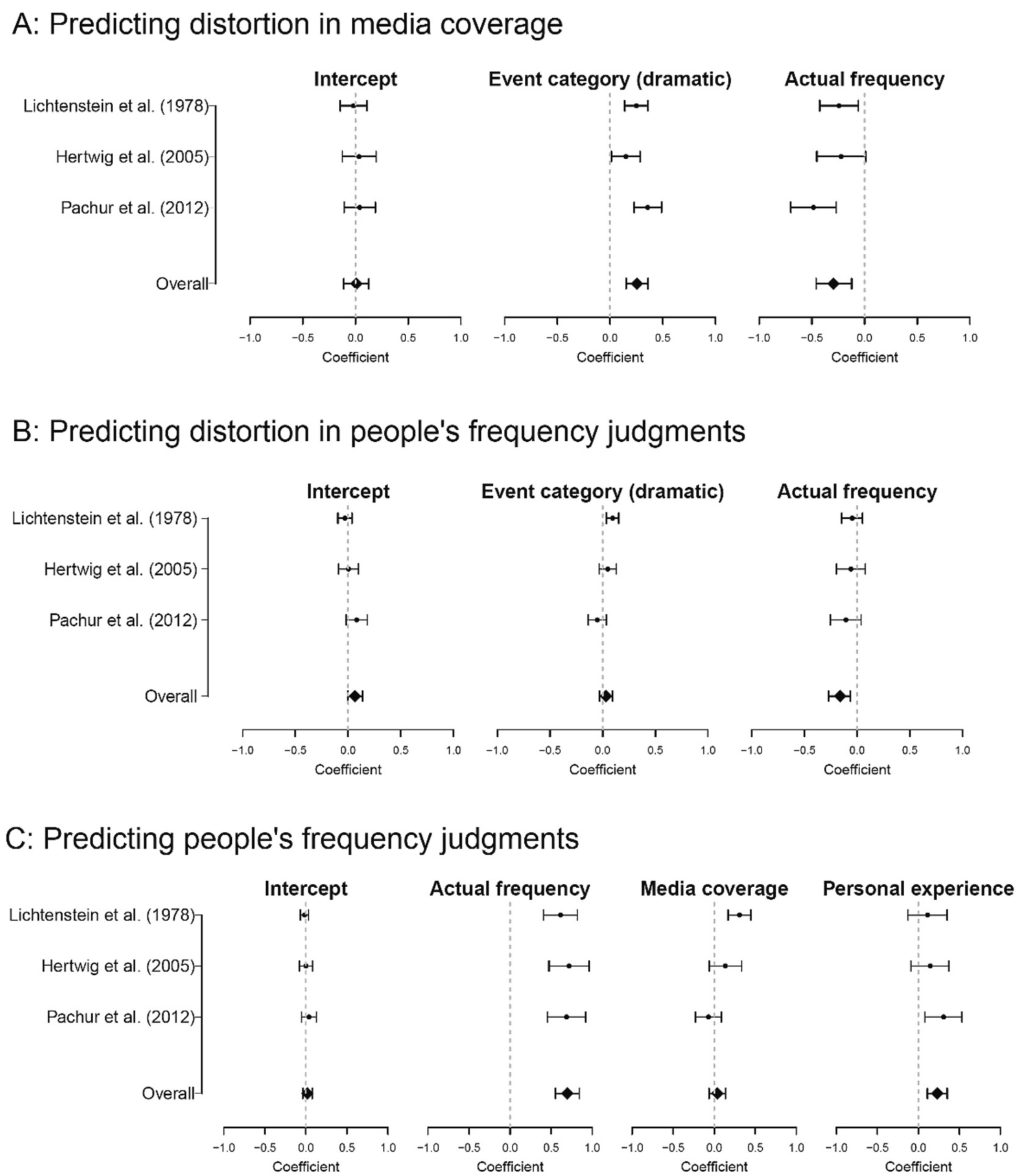

Fig. 3. Estimated regression coefficients for predicting the deviation of the risks' media ranks from the actual ranks (Panel A) and the deviation of the risks' judgment ranks from the actual ranks (Panel B) when using the risks' categorization as dramatic versus nondramatic as predictor. Panel C shows the estimated regression coefficients for predicting the risks' judgment ranks.

Note. Error bars represent the 95% highest density intervals. Shown are the results for the models for each of the three datasets separately as well as for the mixed-effects regression model that estimated an overall effect across the datasets.

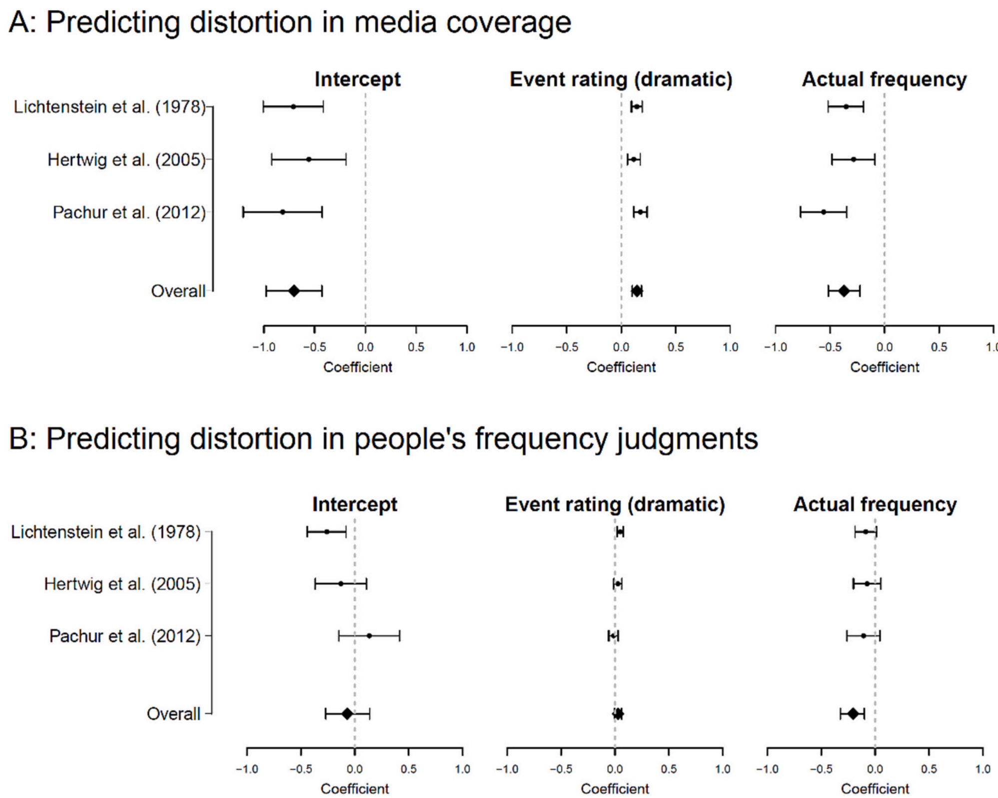

Fig. 4. Estimated regression coefficients for predicting the deviation of the risks' media ranks from the actual ranks (Panel A) and the deviation of the risks' judgment ranks from the actual ranks (Panel B) when using the continuous drama intensity ratings as predictor.
Note. Error bars represent the 95% highest density intervals. Shown are the results for the models for each of the three datasets separately as well as for the mixed-effects regression model that estimated an overall effect across the datasets.

across all three datasets actual frequency was negatively related to the amount of distortion in the media (see Figs. 3 and 4). This indicates that rare risks were more prone to overrepresentation than frequent ones.[2]

What about the distortions of dramatic and nondramatic risks in people's frequency judgments (Figs. 3B and 4B)? For the Lichtenstein et al. (1978) data, there was a credible and positive effect of category—meaning that the relative frequency of dramatic events tended to be overestimated and that of nondramatic events tended to be underestimated. The same held when using the continuous ratings as predictor. The evidence for the effects was moderate (category: $BF_{10} = 8.220$; ratings: $BF_{10} = 6.170$). The analysis thus statistically corroborates the common conclusion from Lichtenstein et al.'s dataset that dramatic and nondramatic risks differ in how they are misjudged. For the other two datasets, however, the analyses indicated no difference between dramatic and nondramatic events; in fact, there was at least moderate evidence for the absence of an effect, for both Hertwig et al. (2005; category: $BF_{10} = 0.217$; ratings: $BF_{10} = 0.138$) and Pachur et al. (2012; category: $BF_{10} = 0.217$; ratings: $BF_{10} = 0.067$). Across the three datasets, the mixed-effects regression yielded overall effects for category of $b = 0.032$ ($HDI_{95\%} = [-0.029, 0.093]$), and for ratings of $b = 0.028$ ($HDI_{95\%} = [-0.004, 0.061]$). There was moderate evidence that the distortion in people's frequency judgments did not differ between dramatic and nondramatic risks (category: $BF_{10} = 0.137$; ratings: $BF_{10} = 0.196$). Figs. 3B and 4B also show that in all three datasets the amount of distortion in people's judgments was negatively related to actual frequency, such that distortions in risk judgments were more pronounced for rare than for frequent causes of death (see Footnote 2). In sum, when considering all the available data on people's frequency judgments for the set of causes of death investigated by Lichtenstein et al., there is no evidence for the widespread notion that people overestimate dramatic risks and underestimate nondramatic risks. As reported in more detail in Appendix C, this conclusion also holds when including the datasets identified in the systematic literature search that collected only frequency judgments for Lichtenstein et al.'s set of causes of death (but no measures of media coverage). In most of these datasets there was no evidence that people overestimate dramatic risks and underestimate nondramatic ones.

The upshot of the analyses is depicted in Fig. 5. It shows, from the mixed-effects regression models estimating overall effects across the three datasets, the conditional effects of category (upper row) and ratings (lower row) on how actual prevalence of the the causes of death is distorted in media coverage (left column) and in people's frequency judgments (right column). More dramatic events tended to be overrepresented in the media relative to their actual relative frequencies and less dramatic events tended to be underrepresented. This difference, however, was not paralleled in the distortions in people's risk judgments: Overestimation and underestimation of relative frequencies of the causes of death were basically unaffected by how dramatic the causes of death are.

In additional analyses, I explored possible factors influencing people's frequency judgments. Fig. 3C shows the results of a regression model that predicted the judgment ranks based on media ranks and the relative ranks according to the number of instances of the causes of death that people recalled from their personal social circles (*social circle*

[2] The likely reason for the negative relationship between the distortions and actual rank is the skew in the distribution of the risks on the different variables, where differences between the risks are fairly small at the lower end of the range and deviations in rank are therefore more likely.

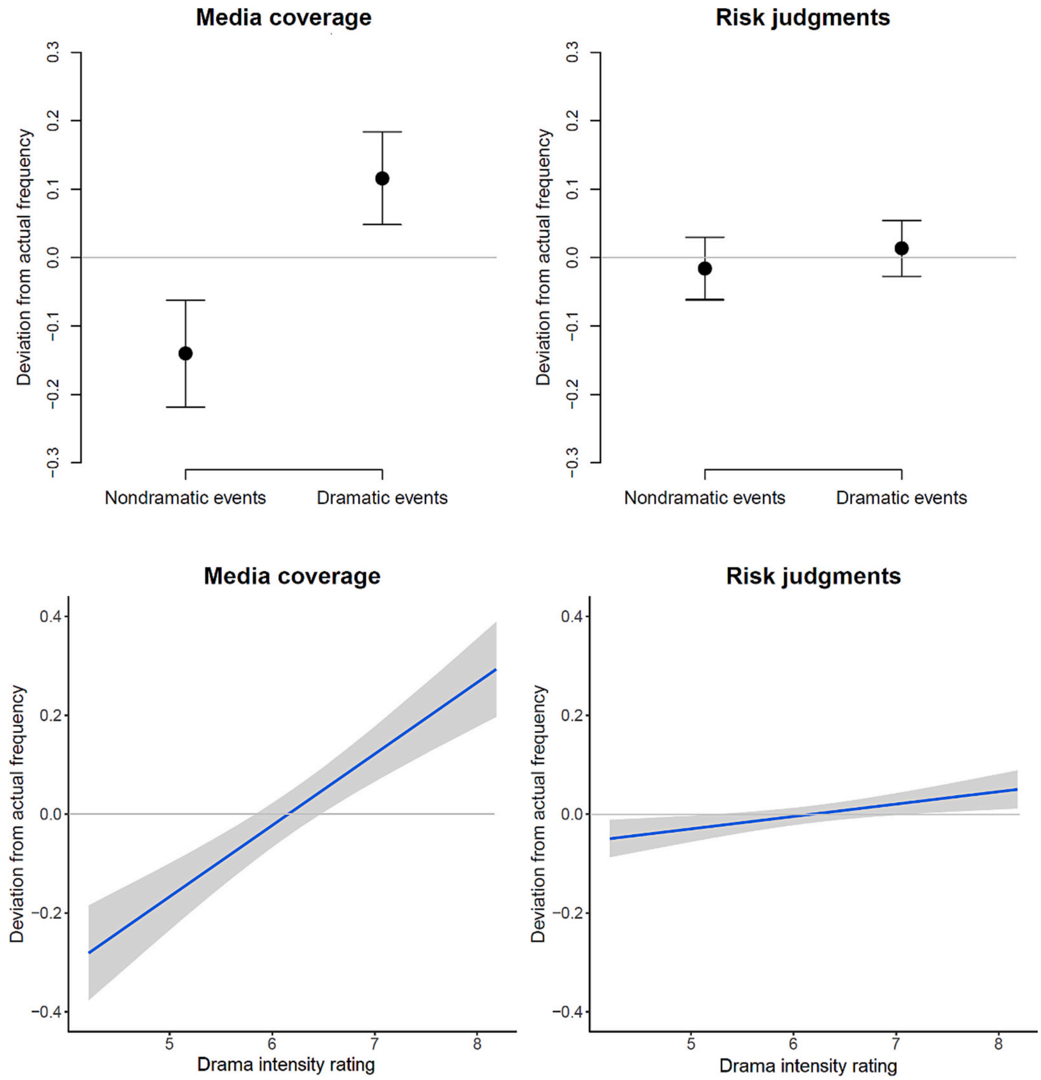

Fig. 5. Distortion of the actual relative frequency of causes of death in media coverage and in people's frequency judgments as a function of whether they are dramatic or nondramatic (upper panels) and of their drama intensity rating (lower panels).
Note. Shown are the deviation of the media ranks (left panel) and the judgment ranks (right panel) from the actual ranks, based on the conditional effects obtained with the mixed-effects regression model that estimated an overall effect across the datasets.

ranks)—a measure that was collected in all three datasets. To evaluate the associations of judgment rank with media rank and social circle rank beyond their shared variance with actual frequency, actual rank was included as a covariate. As can be seen in Fig. 3C, people's frequency judgments were linked with media coverage only in the Lichtenstein et al. (1978) dataset, but not in the other datasets.[3] In mixed-effects modeling across all datasets, the BF_{10} for an association between judgment rank and media rank was 0.17, providing strong evidence against such an association. This is consistent with the result reported above that the distortion difference between dramatic and nondramatic risks in media coverage was not reflected in people's risk judgments. What did predict people's frequency judgments reliably and consistently across all three datasets, however, was social circle rank—that is, people's experiences with the causes of death in their personal social circles. This link was particularly pronounced in the Pachur et al. (2012) dataset. When the effects were estimated across all datasets, the BF_{10} for an association between judgment rank and social circle rank was 119.77, providing very strong evidence for such an association (in additional analyses predicting social circle rank across all datasets, the BF_{10} for the effects of category and ratings were 0.102 and 0.177, respectively; this indicates that people did not recall instances of dramatic and nondramatic events occurring in their social circles differently). In the Discussion section I address the theoretical relevance of this finding for the notion that people rely on the availability heuristic (Tversky & Kahneman, 1973) for their risk judgments.

4. Discussion

A common tale about human risk perception is that people overestimate dramatic, sensational risks and underestimate nondramatic, mundane risks, and that this cognitive distortion is due to unrepresentative media coverage—a view originating from Lichtenstein et al.'s

[3] Analyses predicting the risks' media ranks on the actual frequencies showed that the misrepresentation in media coverage in Lichtenstein et al.'s (1978) dataset was not lower than in the other datasets, with regression coefficients of b = 0.74 ($HDI_{95\%}$ = [0.51, 0.96]), 0.74 ($HDI_{95\%}$ = [0.50, 0.99]), and 0.48 ($HDI_{95\%}$ = [0.18, 0.78]) for Lichtenstein et al., Hertwig et al. (2005), and Pachur et al. (2012), respectively.

(1978) seminal investigation. The current analysis tested to what extent this "most consistent finding of risk perception research" (Gardner, 2008, p. 67) is statistically reliable and replicates in other studies. In addition to Lichtenstein et al.'s data I analyzed the two other existing datasets that collected both frequency judgments and measures of media coverage for the causes of death investigated by Lichtenstein et al. Despite the considerable changes in the media landscape in the decades between Lichtenstein et al.'s original study and Hertwig et al. (2005) and Pachur et al. (2012), the current analysis indicated clear and consistent evidence that the media strongly overrepresents dramatic and underrepresents nondramatic risks. This pattern was robust across the various measures of media coverage that were collected in the datasets—including both objective measures (mention frequency, inches devoted to a risk; see Appendix D) and subjective, memory-based measures, as well as various types of media (newspapers, TV, internet, novels, and movies). Importantly, however, the distortions in media coverage were not paralleled by differences between dramatic and nondramatic events in terms of how they are distorted in people's frequency judgments. Although the relative frequency of dramatic risks was overestimated and that of nondramatic risks was underestimated in Lichtenstein et al.'s data, this pattern did not emerge in the other datasets; meta-analytically combining the effects across all three datasets, there was evidence for the absence of a difference between dramatic and nondramatic risks in how they are distorted in people's risk judgments.

The current analysis thus points to a limited replicability of the empirical findings that underlie the commonly held view that intuitive judgments of risk frequencies echo a distorted representation of risks in the media. This conclusion does not necessarily challenge the evidence that the media can have an important influence on public agenda setting or people's level of concern more generally (e.g., Bartels, 1993; Mazur, 2006; Tyler & Cook, 1984), or that some media (e.g., television) can inform people's impressions of the frequency of specific events (e.g., Shrum & O'Guinn, 1993). It also does not mean that the media may not distort people's assessments of subjective risk (i.e., how subjectively "risky" an event or technology is; Slovic, 1987) or beliefs about potential harms, or that media campaigns to raise awareness of underrated risks (e.g., smoking, HIV, STDs) will be ineffective. Judgments of the subjective risk of health hazards may well be based on different mechanisms and influenced by different factors than are judgments of the frequencies of these hazards. But note that existing evidence is mixed on the link between media coverage and ratings of subjective risk (see also Wahlberg & Sjöberg, 2000). For instance, Englander, Farago, Slovic, and Fischhoff (1986) observed differences in risk perception between American and Hungarian respondents that were consistent with differences between the countries in media coverage. In a longitudinal study by Sjöberg et al. (1996; cited in Boholm, 1998), however, there was no link between changes in media coverage and changes in risk perception.

The current findings have implications for psychological models of judgment under uncertainty. Lichtenstein et al.'s (1978) conclusion that dramatic events are both overreported in the media and overestimated in frequency by people has often been marshalled as evidence for the availability heuristic (Tversky & Kahneman, 1973). Although the present findings do not contradict the general notion underlying the availability heuristic, they suggest that people's reliance on available samples is more sophisticated than the mechanism described by Tversky and Kahneman. Given that risk frequency judgments do not echo the media's distorted representation of risks, apparently people do not simply rely on any instances that are mentally available to them. Rather, they may actively discount even highly available samples—for instance, because they have concerns about the usefulness of the information for the judgment task at hand—and instead rely on other samples. The notion of selective reliance on mental samples is further supported by the finding of the current analysis that the available samples of instances from people's personal social networks are a much stronger predictor of the frequency judgments than are available samples from the media (Fig. 3C; see also Pachur, Hertwig, & Rieskamp, 2013; Schulze, Hertwig, & Pachur, 2021).[4] It also underscores that just as availability can be operationalized in different ways (e.g., Fiedler, 1983; Sedlmeier, Hertwig, & Gigerenzer, 1998; Wänke, Schwarz, & Bless, 1995), the availability of risks in people's minds can in principle be driven by different types of knowledge—including knowledge of instances obtained from media reports and knowledge of instances experienced directly in one's personal social circles.

Further, the results are at odds with the idea that people are usually metacognitively myopic with regard to the usefulness of the information samples available to them (Fiedler, 2000; Fiedler et al., 2023; Juslin, Winman, & Hansson, 2007). An important issue for future research is to examine the conditions under which people are or are not sensitive to distortions in their mental samples and adjust their reliance on them accordingly (e.g., potentially depending on whether the origin of a sample can be traced unambiguously). In general, models of frequency judgments should include a metacognitive control mechanism that monitors the (subjective) validity of the samples of information—for instance, by tracking and considering the context in which the instances were encountered (e.g., Dougherty, Gettys, & Ogden, 1999).

The current work highlights that in future research it will be useful to more clearly delineate the concept of dramatic risks. What characteristics make a risk dramatic enough to lead to it being overrepresented in the media (Soroka, 2012)? Does an event need to evoke strong emotions? Does it need to be memorable? To make conceptual progress, one could also link the notion of dramatic risks to the dread component identified with the psychometric paradigm on risk perception (Slovic, 1987). Indeed, some of the characteristics that Lichtenstein et al. (1978) and Combs and Slovic (1979) used to distinguish dramatic and nondramatic risks (e.g., catastrophic potential, dread; see Table A1) overlap with characteristics highlighted by the psychometric paradigm. The results from the current study (Appendix B), in which drama intensity ratings were obtained for causes of death, may serve as a useful starting point for more targeted investigations into the anatomy of the concept. For instance, the finding that cancers generally received high ratings (Fig. 1) suggests that painful deaths are perceived as particularly dramatic. The high ratings for fire and flames, fireworks, electrocution, drowning, and flood might suggest that the degree to which a cause of death can be visualized could be another important factor. A better understanding of the concept of dramatic risks might also be reached by large-scale analyses of latent semantic patterns in which the events are embedded in natural language (e.g., Aka & Bhatia, 2022; Bhatia, 2019; Demszky, Yang, Yeager, et al., 2023; Li, Hills, & Hertwig, 2020).

In Lichtenstein et al.'s (1978) analysis, frequency judgments were examined on the aggregate level; for comparability, this approach was also adopted in the current analysis (the individual-level data of Lichtenstein et al. are not available). A limitation of that approach, however, is that patterns arising on the aggregate can be misleading with regard to patterns on the level of individual participants (e.g., Estes & Maddox,

[4] Might this reliance on availability through knowledge of instances in personal social networks be adaptive? As reported in Section 3, regression coefficients linking media coverage to actual frequencies were $b = 0.48$–0.74. An analogous regression analysis linking the social circle ranks and actual ranks yielded somewhat higher regression coefficients, with $b = 0.92$ ($HDI_{95\%}$ = [0.79, 1.05]), 0.77 ($HDI_{95\%}$ = [0.56, 0.97] and 0.80 ($HDI_{95\%}$ = [0.59, 1.00]) for the Lichtenstein et al. (1978), Hertwig et al. (2005), and Pachur et al. (2012) datasets, respectively. This suggests that availability through people's knowledge of relevant instances in their personal social circles may be a more valid cue to the frequency distribution of risks in the population than availability through the amount of media coverage—and that people's stronger reliance on the former could thus be adaptive.

2005). However, Hertwig et al. (2005) and Pachur et al. (2012) analyzed their participants' risk judgments on both the aggregate and the individual level and found that the conclusions were similar. This suggests that the aggregate-level patterns represent the central tendency of individual data well and that the current analyses are not based on a statistical artefact of aggregation. Nevertheless, a rigorous examination of the cognitive mechanisms underlying people's judgments requires a consideration of individual-level data.

Another methodological issue in the current analysis is that using the relative ranks of the risks to quantify distortions in media coverage and people's frequency judgments might be too insensitive to detect distortions and differences between dramatic and nondramatic risks. Distortions in ranks capture shifts in the relative position of the risks on the different variables, but ranks are insensitive to distortions that do not alter the relative position of the risks. This does not seem to be problematic for the current analysis, however, as shown by the results for media coverage and frequency judgments in Lichtenstein et al. (1978), where the rank-based approach indicated differences between the distortion of dramatic and nondramatic events. An alternative approach to using ranks would be to analyze the risks' absolute values on the variables and log-transform them to address the skew in their distributions, but that approach would not be without its own problems. In both Hertwig et al. (2005; see their Table 1) and Pachur et al. (2012; see their Table 4) some of the causes of death have entries of zeros and would have to be excluded from the analysis (as the log of zero equals infinity), thus reducing statistical power and comparability with the Lichtenstein et al. data. In addition, a log transformation complicates the interpretation of distortions in the distribution of the risks; distortions in terms of ranks, by contrast, are straightforward to interpret. On balance, using ranks seems a useful compromise—and given that the ranks revealed differences between dramatic and nondramatic risks in one of the datasets, it seems to be generally able to detect systematic patterns in how dramatic and nondramatic risks are distorted in media coverage and people's frequency judgments.

People's intuitive judgments and risk perceptions are not perfect (e.g., Gigerenzer, 2015; Groß, Kreis, Blank, & Pachur, 2023). However, the commonly held notion that people's reasoning about risks is warped by how dramatic the risks are, potentially reflecting and amplifying biases present in media coverage, is not supported by the available data. This means that efforts to rectify risk perception by encouraging more proportional reporting of risks in the media are likely to be met with limited success. In the end, inaccuracies in risk perceptions may reflect a lack of information rather than people's inability to shield themselves from a distorted media environment.

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CRediT authorship contribution statement

Thorsten Pachur: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Visualization, Writing – original draft, Writing – review & editing.

Data availability

The data and analysis code can be retrieved via https://osf.io/u4d7g.

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Appendix A. Procedure for categorizing causes of death as dramatic or nondramatic

Table A1 shows the statements in Lichtenstein et al. (1978) and Combs and Slovic (1979) that served as a basis for categorizing the causes of death investigated by Lichtenstein et al. as dramatic or nondramatic. The statement indices in Table 1 in the main text indicate which statements were used for categorizing each cause of death. Fireworks, electrocution, nonvenomous animals, and venomous bite or sting were categorized as dramatic because they belong to subcategories of the category "accidents" ("contact with heat or hot substance," "exposure to electric current," "contact with venomous animals and plants") according to the ICD-10 classification (https://icd.who.int/browse10/2019/en#/X30-X39). Drowning, excess cold, flood, lightning, and tornado were categorized as dramatic because they are natural disasters or belong to a subcategory of the ICD-10 category "accidents" ("exposure to forces of nature").

Table A1
Statements in Lichtenstein et al. (1978) and Combs and Slovic (1979) used to categorize the causes of death as dramatic or nondramatic.

Statement index	Statement	Source
1	"… the frequencies of dramatic events such as cancer, homicide, or multiple-death catastrophes, which tend to be publicized disproportionately…"	LSFLC (p. 552)
2	"The error may stem from the dramatic nature of leukemia and the greater amount of media publicity it receives, or it may stem from the fact that accidental falls are common but usually non-fatal."	LSFLC (p. 573)
3	"In Experiments 1 and 3 subjects appeared to underestimate (relative to the regression line) the frequencies of deaths due to events that are common in nonfatal form, such as smallpox vaccination and asthma."	LSFLC (p. 569)
4	"Again, it is easy to see how media publicity regarding poisoning and the dramatic nature of the event could cause subjects to overestimate it compared to the drab, undramatic, perhaps old-fashioned disease, tuberculosis."	LSFLC (p. 573)
5	"Most of the causes of death that were underestimated (relative to the regression line)—asthma, tuberculosis, diabetes, stomach cancer, stroke, and heart disease—seem to be undramatic, quiet killers."	LSFLC (p. 575)
6	"… among the most overestimated causes of death (relative to the regression line) were botulism, tornado, flood, homicide, motor vehicle accidents, all accidents, and cancer. These are all sensational events."	LSFLC (p. 575)
7	"All forms of disease appeared to be greatly underreported while violent, often catastrophic events, such as tornadoes, fires, drownings, homicide, motor vehicle accidents and all accidents stood out as being overreported."	CS (p. 841)
8	"Violent, often catastrophic causes of death such as homicides, natural disasters, and accidents…"	CS (p. 843)

Note. LSFLC = Lichtenstein et al. (1978); CS = Combs and Slovic (1979).

Appendix B. Description of the study collecting continuous drama intensity ratings

B.1. Participants

For the online study, 250 participants ($M = 38.62$ years, $SD = 13.46$; 133 female, 112 male, 5 nonbinary) from the United States (with English as native language) were recruited via Prolific. The median completion time was about 3 min and participants were remunerated with £1.17 for participating.

B.2. Procedure

The survey was programmed on SoSci (https://www.soscisurvey.de/). After reading general instructions on the study and data security, participants provided consent. They were then presented with the 41 causes of death used by Lichtenstein et al. (1978) on a single page and in random order. The instruction read:

> Different risks differ in how "dramatic" they are perceived to be. In the following, please indicate for each of the following 41 causes of death how "dramatic" you find it, using the scale from 1 ("Not dramatic at all") to 9 ("Very dramatic"). We are interested in your intuitive impression of each risk, and there are no right or wrong answers.

After rating each cause of death, participants provided demographic information (age, gender, education) and indicated whether they had worked seriously on the task or merely clicked through (all participants indicated that they had worked seriously on the task).

Appendix C. Description and analysis of the datasets that collected only frequency judgments

As mentioned in Section 2.1, the literature search also identified articles that collected frequency judgments for the causes of death investigated by Lichtenstein et al. (1978) but no measures of media coverage. These studies were not included in the main analyses as this would distort the comparability of the patterns in media coverage and patterns for frequency judgments. Nevertheless, it might be informative to derive an overall estimated effect of how the distortions in the frequency judgments differ between dramatic and less dramatic causes of death when these studies are included. In the following, I provide information on the individual datasets, report the results for these studies, and report on the estimated effects when these studies and those from the main analyses are meta-analytically combined.

In Morgan et al. (1983), 17 participants provided estimates of the annual mortality rates for Lichtenstein et al.'s (1978) 41 causes of death in the U.S; to obtain an approximate measure of the actual frequencies, each participant was given a sample of four causes of death with the instruction to provide an analytical estimate. The dataset by Benjamin et al. (2001) involved responses by 98 participants who were asked to "estimate, as well as you can, the number of people in the United States who die each year from each cause" (p. 51). The actual frequencies were taken from the most recent official statistics for a single year. In Armantier (2006) there were a total of six conditions; in each condition 35 participants were asked to evaluate the total number of deaths in the year 1999. The conditions differed in terms of the reference group to which the estimate referred (U.S. population-wide, own-age cohort, different age cohort) and whether there was a second condition (which was hypothesized to lead to different types of distortions). In the present analyses, I considered only the three conditions (Treatments 1, 4, and 6) in which participants were asked to estimate the number of deaths in the U.S. population and in which the estimation task was not preceded by an estimation task referring to a different reference group (to ensure comparability with the set-up in Lichtenstein et al.). These conditions included 39 causes of death, of which 36 were also investigated by Lichtenstein et al. (1978). I considered the estimates for these 36 causes of death. The estimates were evaluated relative to official statistics for the year 1999. Hakes and Viscusi's (2004) investigation involved 23 of Lichtenstein et al.'s causes of death; 462 participants were asked to estimate the number of people who died from each cause of death. The responses were compared to the official statistics for the year 1993. Finally, the datasets by LaCour and Davis (2020) consisted of data from two online experiments (conducted via MTurk). In Experiment 1, 158 participants estimated the annual mortality rate for 40 of Lichtenstein et al.'s causes of death in the U.S. In Experiment 2, 109 participants provided estimates for 23 of the causes of death. The estimates were evaluated relative to official statistics from various sources.

Fig. C1 plots, separately for each of the additional datasets, each risk's actual rank against its judgment rank, with circle markers for dramatic risks and triangle markers for nondramatic risks. Fig. C2 displays the results of the regression analyses for all studies that collected frequency judgments for the causes of death investigated by Lichtenstein et al. (1978) as well as the overall effects. To estimate the overall effects, I conducted mixed-effects regression models with random intercepts for the different causes of death as well as random intercepts for datasets. As can be seen, the additional datasets show a similar pattern as the three focal datasets of Lichtenstein et al. (1978), Hertwig et al. (2005), and Pachur et al. (2012), with only weak effects of how dramatic a cause of death is on how it is overestimated or underestimated. Across all studies, the overall effect was not credible for category, $b = 0.051$ ($\text{HDI}_{95\%} = [-0.005, 0.107]$), and credible for ratings, $b = 0.034$ ($\text{HDI}_{95\%} = [0.007, 0.062]$). The Bayes factors (BFs) for the effects of category and ratings in the different datasets are reported in Table C1. For 10 of the 16 additional analyses there was moderate evidence for the absence of an effect of how dramatic a cause of death is, with the remaining effects providing inconclusive evidence. The BFs of the effects across all 11 datasets point to the absence of a difference between dramatic and nondramatic events, but are inconclusive.

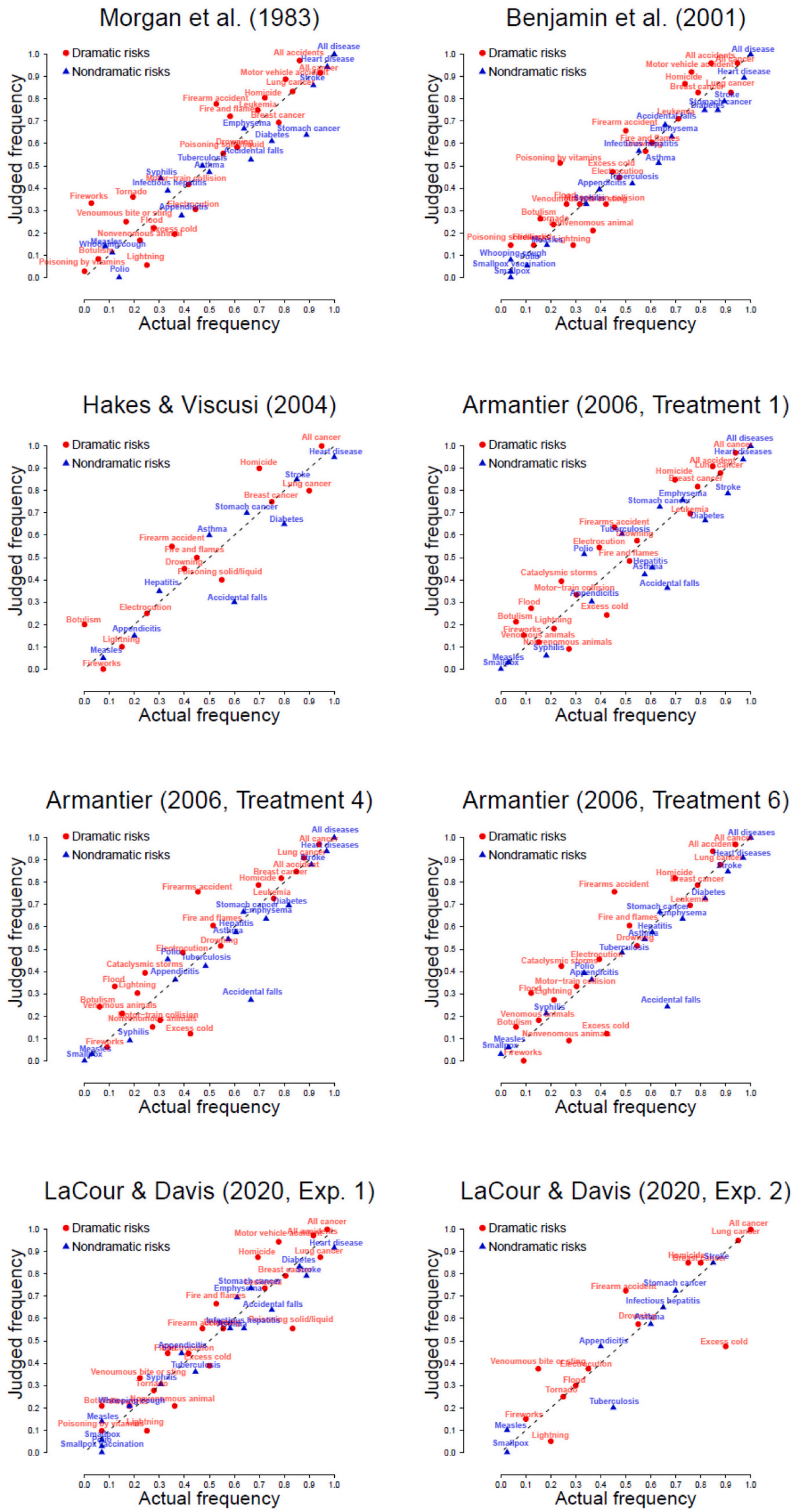

Fig. C1. Judgment rank (according to people's frequency judgments) of the causes of death investigated by Lichtenstein et al. (1978) plotted against their actual ranks for the datasets that collected only frequency judgments.

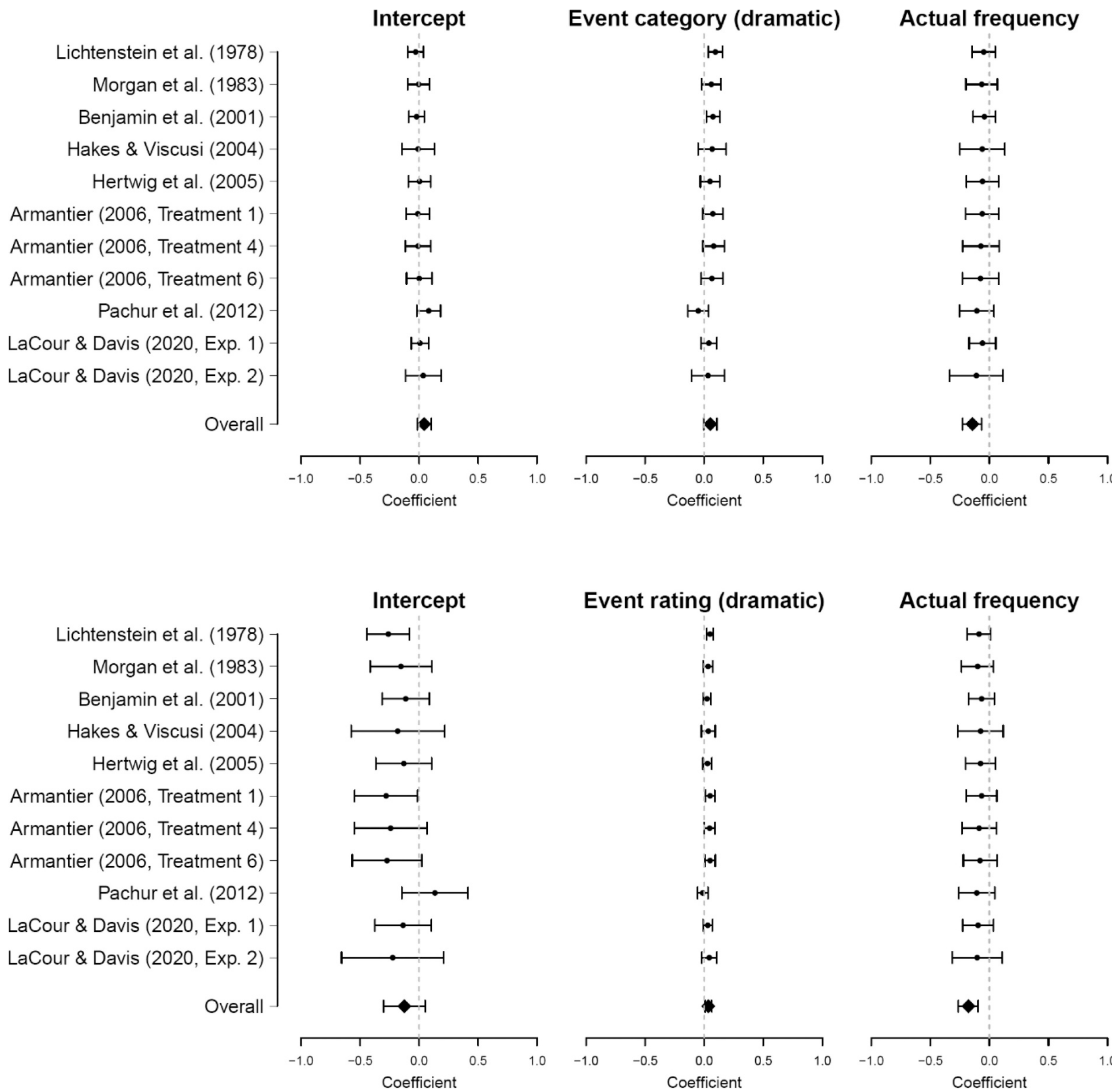

Fig. C2. Estimated regression coefficients for predicting the deviation of risks' judgment rank from their actual rank, with all datasets identified in the literature search that collected frequency judgments for the causes of death investigated by Lichtenstein et al. (1978). The upper plot shows results when using category as predictor; the lower plot shows results when using ratings as predictor.
Note. Error bars represent the 95% highest density intervals. Shown are the results for the models for each of the 11 datasets separately as well as the mixed-effects regression model that estimated an overall effect across the datasets.

Table C1
Bayes factors (BFs) for category (dramatic vs. nondramatic) and continuous drama intensity ratings as predictors of the distortion of the frequency judgments for all datasets that collected frequency judgments for the causes of death investigated by Lichtenstein et al. (1978).

	BF_{10} for effect of predictor	
Dataset	Category	Ratings
Lichtenstein et al. (1978)	8.220	6.171
Morgan et al. (1983)	0.321	0.185
Benjamin et al. (2001)	1.916	0.123
Hakes and Viscusi (2004)	0.297	0.156
Hertwig et al. (2005)	0.217	0.138
Armantier (2006, Treatment 1)	0.499	1.014
Armantier (2006, Treatment 4)	0.541	0.418
Armantier (2006, Treatment 6)	0.323	0.699
Pachur et al. (2012)	0.217	0.067
LaCour & Davis (2020, Exp. 1)	0.170	0.165
LaCour & Davis (2020, Exp. 2)	0.191	0.208
Overall	0.397	0.671

Appendix D. Results for Different Operationalizations of Media Coverage in Lichtenstein et al. (1978)

As mentioned in Section 2.2.3 of the main text, Lichtenstein et al. (1978) considered three operationalizations of media coverage: ratings of how often participants had heard about a given risk as a cause of death in the media (*indirect experience*), the total number of deaths reported for a year (*media frequency*), and the square inches of reporting devoted to the causes of death, excluding photographs (*media inches*). Fig. D1 shows the results of the regression analyses predicting the deviation between media rank and actual rank for the three operationalizations. As can be seen, the conclusions are the same across all three operationalizations. When using category as predictor, the Bayes factors (BFs) for an effect of how dramatic a cause of death is on the distortion in media coverage were $BF_{10} = 748.274$ for indirect experience, $BF_{10} = 7.240$ for media frequency, and $BF_{10} = 8.005$ for media inches. When using the ratings as predictor, the Bayes factors were $BF_{10} = 28{,}134.569$ for indirect experience, $BF_{10} = 66.089$ for media frequency, and $BF_{10} = 82.364$ for media inches.

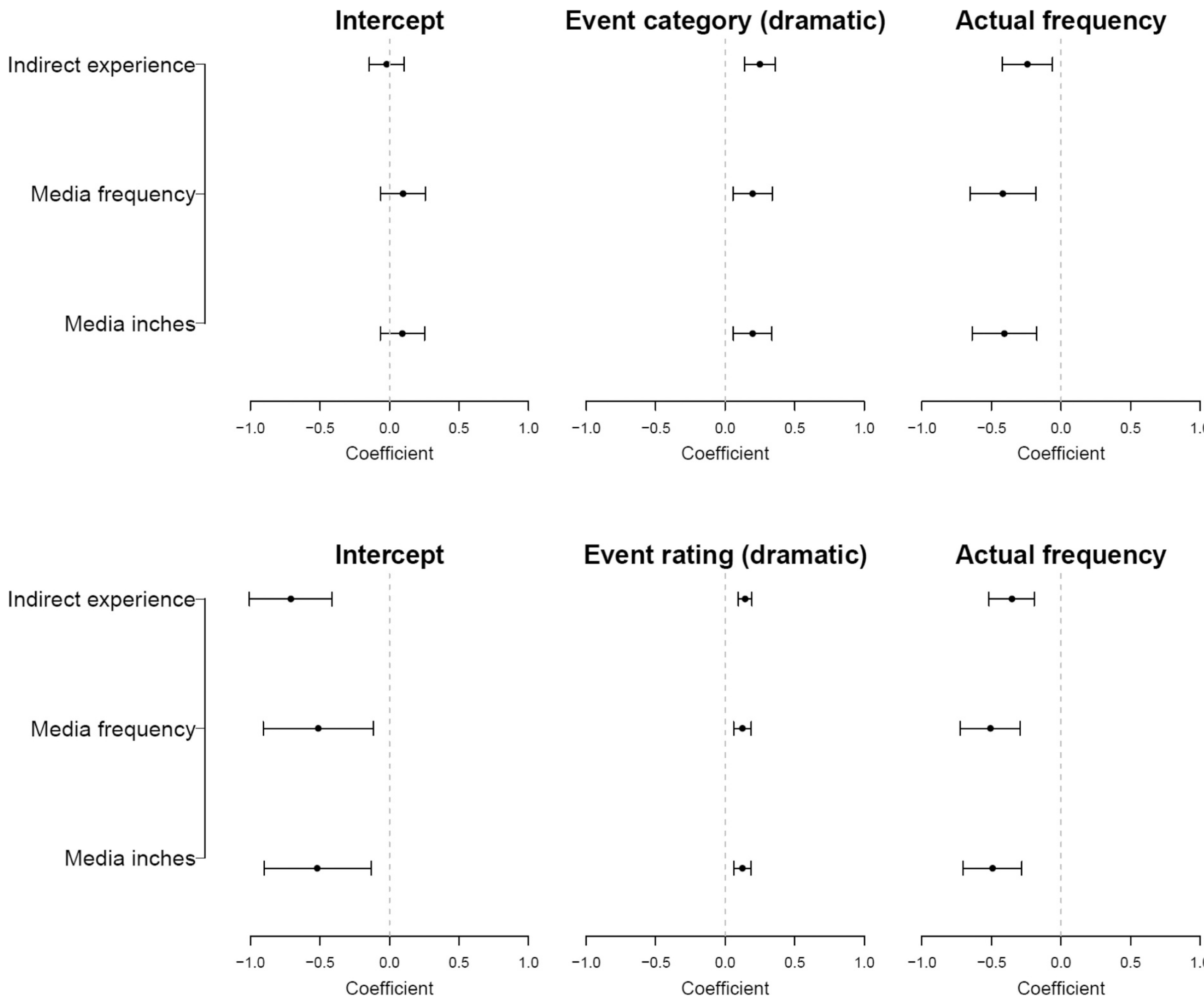

Fig. D1. Estimated regression coefficients for predicting the deviation of risks' media rank from their actual rank for the three operationalizations of media coverage in Lichtenstein et al. (1978). The upper plot shows the results when using category as predictor; the lower plot shows the results when using ratings as predictor. *Note.* Error bars represent the 95% highest density intervals.

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