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ORIGINAL ARTICLE

Objective risk exposure, perceived uncontrollable mortality risk, and health behaviors

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Abstract

Aim Perceived uncontrollable mortality risk (PUMR) refers to people's beliefs regarding their risk of death due to factors outside of their control. Previous theoretical models and empirical studies provide evidence that those with greater PUMR are less motivated to invest in preventative health behaviors, but little is known about how accurately people estimate PUMR compared to objective measures of risk exposure, an important consideration for interventions designed to address the link between PUMR and health behavior. Here, we explore how objective risk indices and personal characteristics relate to PUMR.

Subject and methods We performed a series of pre-registered analyses on a US-representative longitudinal study ($N = 915$), connecting these results to external data from the Global Burden of Diseases, Injuries, and Risk Factors Study.

Results We show that (Study 1) PUMR is associated with objective measures of risk exposure, and that (Study 2) perceptions of risk due to disease drive PUMR, and more educated individuals report less perceived risk. Additionally, we find that (Study 3) estimates of PUMR are relatively stable over a 4-month period ($R = 0.7$), indicating that behaviors influenced by PUMR are likely to persist over time. Finally, we show that (Study 4) those who believe they are at greater risk of dying due to factors outside of their control (i.e., greater PUMR) are less likely to engage in general health behaviors.

Conclusion By assessing the determinants of PUMR, we can create data-driven policy solutions that lead individuals to more accurate mortality risk assessments and improved health behavior.

Keywords Risk perception · Health behaviors · Mortality risk · Extrinsic mortality · Uncontrollable mortality

Background

In the United States, chronic diseases lead to 7 out of every 10 deaths each year, yet these illnesses are largely avoidable (Centers for Disease Control and Prevention 2022). By maintaining a healthy diet, exercising, and avoiding tobacco and excessive alcohol consumption, individuals can reduce their controllable mortality risk from developing the most common, deadly chronic diseases by up to 80% (Al-Maskari 2010). Still, individuals vary considerably in the amount of effort they exert to achieve positive health outcomes. Surprisingly, uncontrollable mortality risks (e.g., air pollution, violence, or environmental hazards) can influence individuals' motivation to engage in health behaviors that mitigate controllable risks. If an environment is sufficiently hostile, such that an individual has a high risk of death regardless of their behavior, then it makes little sense for them to invest in their long-term future. Both behavioral ecological models and empirical studies have indicated the importance of uncontrollable mortality risks for influencing health-oriented behaviors (Nettle 2010; Uggla and Mace 2015). Pepper and Nettle (2014a) presented a novel method to measure perceived uncontrollable (previously extrinsic) mortality risk (PUMR): that portion of perceived mortality risk that an individual believes they cannot reduce by their behavior. As predicted by theoretical models, they found that

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PUMR was higher for those of lower socioeconomic status and that PUMR mediated the well-documented relationship between socioeconomic status and health-oriented behavior. While these studies found that increased PUMR is associated with deleterious health behaviors (e.g., Brown et al. 2021; Brown and Pepper 2023; Pepper and Nettle 2014b), no work has explored how PUMR relates to uncontrollable mortality risks within one's community. Understanding how PUMR maps to objective measures of mortality risk will enable community leaders to target identified misconceptions regarding health risks, leading to downstream improvements in population health.

Previous work has shown reliable associations between objective risk measures and subjective perceptions of risk for specific causes. A systematic review of 38 studies found an association between air pollution, as measured by particulate matter, and perception of risk for this cause (Cori et al. 2020). Other work has found similar relationships for water quality: individuals from communities with known water contamination problems perceived their drinking water to be riskier than those from communities without such issues (Anadu and Harding 2000), though past problems with water quality provide just one of many contributing factors to individuals' risk estimates; other factors include exposure to different media information and attitudes toward water chemicals (de França Doria 2010). Finally, subjective perceptions of occupational risks have been found to reflect the injury incidence rate of different departments within an organization (Leiter et al. 2009). These findings indicate that subjective perceptions of individual sources of risk are somewhat reflective of objective environmental risk factors in their different domains. However, the extent to which these individual risks contribute to the more general PUMR is still unknown.

Here we explore the relationship between PUMR, perceptions of uncontrollable risks from specific causes, and more objective measures of risk, using data from the Global Burden of Diseases, Injuries, and Risk Factors Study (GBD) 2019 (Murray et al. 2020). The GBD study provides a standardized and comprehensive list of 87 risk factors for over 200 countries and all 50 US states. We use GBD's summary exposure values (SEV) as our measures of uncontrollable risk for each participant, limiting the dataset to just the US states as our sample is entirely from the United States. Each SEV is tailored to a specific risk factor within a location and is also differentiated by sex and age. As such, they provide useful estimates about an individual's exposure to a variety of risks. In this analysis, we will consider one higher-level SEV, environmental/occupational risks, which is a composite of several specific risks (e.g., lead exposure, occupational carcinogens, nonoptimal temperatures). We expect the environmental/occupational risk SEV to be associated with PUMR, as it provides an index of those risks that are not classified by the GBD project as being due to an individual's behavior. As such, it maps onto the definition of perceived uncontrollable (or extrinsic) mortality risk as being that which is not ameliorated by the behavior of the affected individual (Nettle 2010; Pepper and Nettle 2014a). We also consider three risks that were associated with subjective perceptions of risk in previous work (Cori et al. 2020; Anadu and Harding 2000; Leiter et al. 2009): air pollution, unsafe water source, and occupational risks, to test their association with our measures of perceived mortality risk from each of these sources.

Understanding the extent to which perceptions of risk map onto ecological conditions may be essential for effectively designing interventions to improve health behaviors. Individuals can either under- or overrate the threat of a particular hazard, resulting in mismatches between perceptions and objective measures of risk. In these situations, informational interventions aimed at raising or lowering the salience of the hazard will help people to behave appropriately. Conversely, risks for which there are strong associations between objective measures and perceptions may prove useful to inform our understanding of what features make a risk easier to accurately estimate. Lessons gained from such examples can be employed in designing effective informational interventions. By targeting these misconceptions and reducing risks, when possible, community leaders can directly target PUMR, thereby fostering improved public health.

There is an unequal distribution of risk across society that leads to differences in certain groups' perceptions of risk (Beck 1992). For example, individuals with stable, high incomes (or accumulated wealth) have more resources, which enable them to more easily reduce their exposure to morbidity and mortality risk from a variety of causes. Indeed, higher income has been found to correlate with a reduced perception of several types of risks (e.g., perceived threat from environmental risks, Lo 2014). Other demographic characteristics are associated with differences in individuals' perceptions of safety. For example, education levels are associated with differences in perceived risks from water pollution (Jones et al. 2018), COVID-19 (Rattay et al. 2021), and climate change (Sun and Han 2018). For these reasons, income, wealth, and education will be important control variables for our analyses. In addition to these, there are well-documented age and sex differences in risk perception, including toward health risks (Kim et al. 2018) and risky driving (Rhodes and Pivik 2011). We will also control for these factors in our analysis.

What is seen as an uncontrollable risk may also vary subjectively across people. Identifying whether certain risks are widely perceived as more uncontrollable than others may help us to understand the relationships between perceptions of risk and subsequent health behaviors. For example, those who believe that their risk of dying from

an infectious disease is beyond their personal control may be less motivated to engage in the precise health behaviors likely to reduce their risk. In such cases, interventions tailored to emphasize the extent to which the risks of infectious disease are controllable and modifiable may prove effective. We will analyze longitudinal data for PUMR to determine the stability of these risk perceptions over time. If PUMR fluctuates appreciably over time, it is likely to be responsive to short-term informational interventions aimed at increasing perceived controllability of some risks. Alternatively, if perceptions are more entrenched, altering perceptions of control may require longer-term structural interventions to influence longstanding risk beliefs.

In summary, PUMR is known to be associated with health behavior, but no work has previously been done to explore how PUMR relates to objective measures of risk exposure. Here, we seek to begin this exploration by studying how an individual's PUMR relates to indicators of exposure to risk factors. We hypothesize that perceptions of uncontrollable risk will associate positively with objective measures of risk as measured by GBD SEV values. We also explore how perceived risks from specific causes associate with overall PUMR, assess if PUMR associates with health behaviors, and use a longitudinal survey to explore the stability of PUMR across time. Studying these relationships may shed light on one of the prominent causes behind variation in health-oriented behaviors, providing opportunities to improve population health.

General method

This study was approved by the internal review board at Arizona State University (HRP-503a). Our predictions, measures, and analysis plan are pre-registered with the Open Science Framework (osf.io/wy63d). Any departures from the analysis plan are noted in the change log in the appendix (see Supplemental Method 1).

Sample and recruitment

Participants ($N = 915$) were originally recruited on Prolific and were selected to provide a representative sample of the United States population in terms of age, sex and ethnicity. After the initial survey, participants were contacted on a monthly basis through Prolific's anonymized service that allows researchers to contact past participants. Each survey took participants between 5 and 20 min, and participants were compensated with payment in line with Prolific's ethical payment guidelines. On every survey, participants answered several questions for the present study and for other works. Because of the longitudinal and broad-ranging scope of this sample, we will provide the specific measures used as well as information on the dates and number of participants who answered each item for each study below.

Study 1: objective risk exposure is associated with perceived uncontrollable mortality risk

Our first analysis addresses the hypothesis that perceptions of uncontrollable mortality risk are associated with the reality of objective risk exposure. To do so, we collected data on PUMR, perceptions of specific mortality risks, and a number of control variables. See Fig. 1 for a timeline of all the survey questions. We then analyzed the connection between these risk perception data and the risk exposure SEV data generated by the GBD (Murray et al. 2020).

Measures

Perceptions of uncontrollable mortality risk

Participants provided a measure of perceived uncontrollable mortality risk by reporting their believed likelihood of living to the age of 79 (the current average US life expectancy), given that they make the maximum effort to look after their health (from 0, no chance, to 100, certain; Pepper and Nettle 2014a). We subtract their response to this question from 100

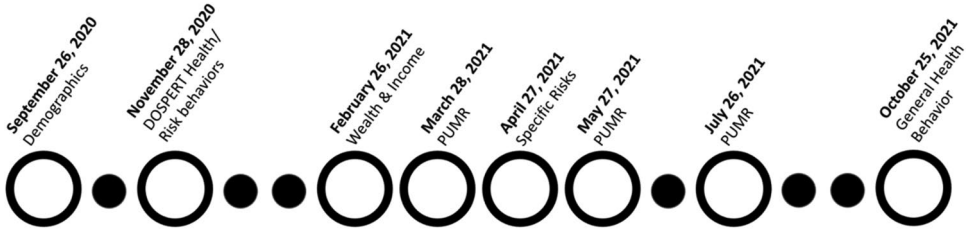

Fig. 1 Timeline of survey questions asked throughout the longitudinal study. Each circle represents a month with the larger, white-filled ones indicating months where survey data were collected and the small black ones indicating intermediate months

to arrive at an estimate of perceived uncontrollable mortality risk. Participants ($N = 448$) answered this question on March 28, 2021. See Supplemental Table S5 for specific wording of each question.

Control variables

A number of individual difference measures can influence both a participant's objective uncontrollable risk exposure and their perceptions of risk exposure. We collected the following factors in various iterations of the survey: sex ($N = 915$), ZIP Code ($N = 815$), education ($N = 915$), age ($N = 914$), savings ($N = 445$), assets ($N = 440$), income ($N = 495$). In our analyses, we convert the savings, assets, and income responses to numeric values by assigning the midpoint of their selection range (i.e., $20,000 for a range from $15,001 to $25,000) for each respondent. Those who selected "Over $200,000" were assigned a value of 250,000. We treat income as a separate variable and sum assets and savings to create an overall wealth variable.

Objective risk exposure: summary exposure values

Summary exposure values (SEV) were taken from the data from the Global Burden of Disease Collaborative Network (GBD 2019). SEV are univariate measures of the relative-risk-weighted prevalence of exposure for particular risks ranging from 0 to 100, where a score of 100 indicates that the entire population is exposed to the maximum risk, and scores of 0 imply that the entire population is at the minimum risk observed. Data for several risks are broken down by state, age group, and sex (GBD, Murray et al. 2020). With these three variables, we tailor SEV values to the demographics and geographic location of each of our respondents based on data from the year 2019. To give an index of overall uncontrollable mortality risk exposure, we use the SEV for environmental/occupational risks. We also use the lower-level air pollution, unsafe water source, and occupational risks SEVs to explore whether objective risk exposures for specific causes predict perceptions of risk for those causes (see Supplemental Method 2).

Analysis

All statistical analyses were conducted in R (R Core Team 2021). The R script used for data analysis is available in a public GitHub repository (https://github.com/CalvinIsch/pumr-omr). The following packages were used for data processing, analysis, and visualization: lme4 (Bates et al. 2015), moments (Komsta and Novomestky 2015), ggplot2 (Wickham 2011), bestNormalize (Peterson and Peterson 2020), tidyverse (Wickham et al. 2019), maps (Brownrigg et al. 2018), leaflet (Cheng et al. 2019), usmap (Lorenzo 2019), geojsonio (Chamberlain and Teucher 2021), sf (Pebesma 2018), rgeos (Bivand et al. 2017), and ggpubr (Kassambara 2020). For the study 1 analysis, we ran an ordinary least squares (OLS) regression. Environmental/occupational risk SEV was used as a predictor variable for perceived uncontrollable mortality risk. Additionally, any of the control variables (sex, education, age, wealth, and income) that were significantly associated with the outcome variable in Spearman's correlation analyses were included in the model as additional predictors. Individuals with missing data on these items were removed from analysis.

Results

Of the participants with complete data ($N = 311$), 157 were female (50%), and the average age was 52 years (SD = 13.9). Participants' mean family income was $69,018 (SD = 58,441), and mean wealth was $177,396 (SD = $162,402). Both perceptions of uncontrollable mortality risk and SEV values varied significantly by state (Fig. 2).

Correlation analysis revealed that wealth ($\rho = -0.11$, $p = .04$), education ($\rho = -0.16$, $p < 0.01$), income ($\rho = -0.12$, $p = .02$), and age ($\rho = -0.10$, $p = .04$) were each significantly negatively correlated with PUMR. That is, wealthier, better educated, and older individuals reported lower PUMR than their poorer, less educated,

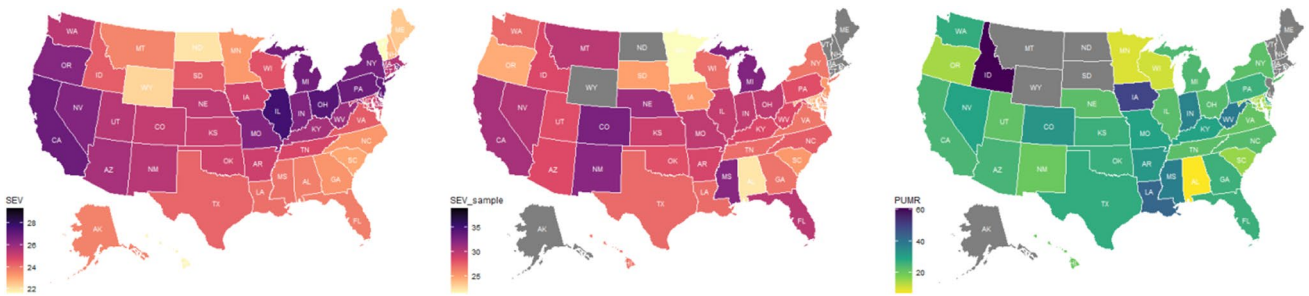

Fig. 2 Average 2019 environmental/occupational SEV values across the United States (left), for our respondents (center), and average PUMR of our participants (right). States without data in our study are marked in gray

and younger counterparts. These items were therefore used as control variables in the main model. To account for non-normality with these data, we normalized wealth, income, age, and PUMR using the *bestNormalize* function before fitting (Peterson and Peterson 2020). We then ran OLS regression to determine if PUMR was predicted by SEV after controlling for the remaining variables. The fitted regression model is presented in Table 1.

The overall regression was statistically significant ($R^2 = .06$, $F(5, 307) = 3.96$, $p = .002$). Environmental/occupational SEV, education, and age, were significant predictors of PUMR. The greater the objective risk according to GBD, the greater an individual's PUMR, indicating some degree of calibration between perceptions and real-world conditions. The more educated and older an individual, the lower their PUMR, as expected from previous research. The remaining variables were not statistically significant predictors of PUMR in the adjusted model. A visual inspection of the residual and qqplot plots (see Supplemental Fig. S1) reveals that all model assumptions are validated. We performed the same procedure on perceptions of mortality risk due to the three specific risk factors: air pollution, unsafe water source, and occupational risks (see Supplemental Method 2, and Supplemental Tables S1–S3). No significant results were found, likely because these risks were much smaller, and our participants had minimal variance among their SEV values for these factors. Specifically, the air pollution (M = 4.91, SD = 1.73), unsafe water (M = 0.34, SD = 0.05), and occupational risk (M = 2.95, SD = 0.93) SEVs all had much lower average values and variance compared with the environment/occupational SEV (M = 28.34, SD = 9.2). As such, these risks were likely less salient and perceived as less risky to participants and a larger sample would be needed to effectively assess if there were associations or not. Indeed, our participants believed that these three risks were less likely than any of the other risks assessed (Table 2). While no statistically significant results were found, every risk analysis produced an association in the direction predicted in the pre-registration.

Table 1 Results of OLS regression predicting perceived uncontrollable mortality risk from environmental/occupational SEV, wealth, education, income, and age

Variable	Standardized **β**	*t* value	*p*
Environmental/occupational SEV	0.25	2.32	0.021
Wealth	0.02	0.28	0.782
Education	−0.09	−2.04	0.042
Income	−0.12	−1.84	0.067
Age	−0.31	−2.55	0.011

Study 2: specific risks and individual difference measures associated with PUMR

What factors are associated with differences in people's perception of their mortality risk? The overall objective uncontrollable mortality risk for an individual is a composite of several specific risk factors. These may be risks in the environment (e.g., air pollution or contaminated water) or those that come from interacting with other individuals (e.g., travel accidents or illegal violence). While the decision-making strategies that people employ to come up with their own perceived estimate of this risk (i.e., their PUMR) are not well understood and may be the result of either simple heuristics or a more complicated risk aggregation function, PUMR is likely associated with lower-level specific risk factors. In study 2, we explore how a number of perceived risk factors relate to estimates of PUMR.

Table 2 Results of OLS regression predicting perceived uncontrollable mortality risk from perceptions of mortality risk to COVID-19, air pollution, contaminated water, illegal violence, travel accident, occupational hazard, natural disaster, and infectious disease, wealth, education, income, and age

Variable	Mean	SD	Standardized **β**	Std. Error (**β**)	*t* value	*P*
COVID-19	15.63	20.71	0.05	0.08	0.67	0.504
Air pollution	10.00	15.32	−0.01	0.11	−0.07	0.944
Contaminated water	8.66	13.69	0.04	0.11	0.34	0.732
Illegal violence	14.83	19.79	−0.13	0.09	−1.49	0.137
Travel accident	21.00	21.24	−0.07	0.09	−0.87	0.385
Occupational hazard	5.59	11.76	−0.11	0.08	−1.42	0.157
Natural disaster	10.35	14.95	0.12	0.09	1.33	0.184
Infectious disease	17.33	21.01	0.22	0.08	2.58	0.011
Wealth	171,467	162,559	0.03	0.08	0.37	0.708
Education	Median: BSc		−0.11	0.04	−2.43	0.016
Income	69,803	57,301	−0.13	0.07	−1.73	0.084
Age	46.19	15.74	−0.11	0.07	−1.59	0.114

Measures

Here, we use the same PUMR and control variables presented in Study 1. Additionally, we asked participants about their perceptions of risk for a variety of factors, to see if any specific risks contributed strongly to their estimates of overall uncontrollable mortality. Specifically, participants provided responses to the following question and risk factors on April 27, 2021:

- *Please indicate your believed likelihood of dying from the following risk factors before the age of 79, provided you do everything you can to take care of your health and ensure your safety: (All responses from 0 [No Chance] to 100 [Certain])*

  - Dying from COVID-19 infection
  - Dying from illness from air pollution
  - Dying from illness from polluted or contaminated water
  - Dying from injuries sustained by illegal violence
  - Dying from injuries incurred in a travel accident (e.g., a motor vehicle, train, or plane crash)
  - Dying from illness or injury caused by your occupation (e.g., injury resulting from heavy machinery or exposure to infection or hazardous chemicals)
  - Dying from natural disaster (such as a flood or forest fire)
  - Dying from infectious disease other than COVID-19

These responses are left in their raw form (0–100) to be directly compared with PUMR from study 1.

Analysis

We first perform correlational analysis to see how strongly each of the specific risk perception variables correlates with the others and to perceptions of overall mortality risk. To address nonlinearity in the data, we use Spearman correlations. We also conduct OLS regression analysis to assess which risk factors remain predictive of PUMR once the others are taken into account. This model contains fixed effects of education, wealth, income, and age.

Results

Spearman correlations reveal that the perceptions of risk due to specific factors are highly correlated with each other. In contrast these perceptions are all only marginally correlated with PUMR (Fig. 3). These small correlations may exist because none of the risks we measured contribute strongly to PUMR. We discuss this in more detail in the general discussion.

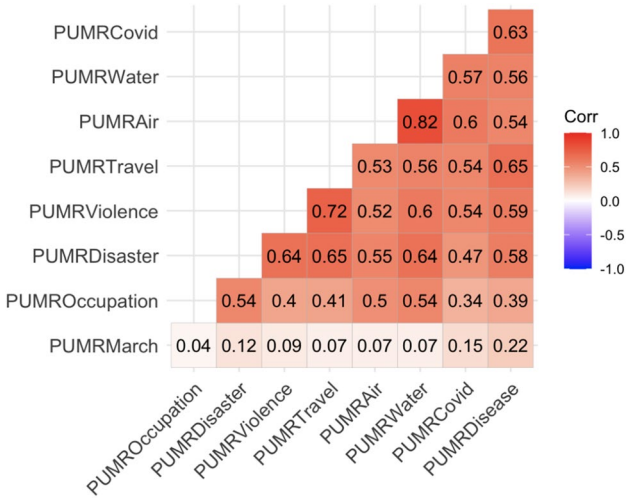

Fig. 3 Correlations matrix between perceptions of mortality risk from specific causes and perception of uncontrollable mortality risk

We next explore how these risk factors predict PUMR when controlling for one another and also when controlling for the same control variables used in study 1 (education, age, wealth, and income). Because the data were non-normally distributed, all of these variables were normalized using the *bestNormalize* function (Peterson and Peterson 2020). We ran OLS regression, and the fitted results are presented in Table 2.

The overall regression model was statistically significant ($R^2 = .11$, $F(12, 287) = 3.05$, $p < .001$). Education ($\boldsymbol{\beta} = -0.11$, $p = 0.02$) and perceived risk of death due to disease ($\boldsymbol{\beta} = 0.22$, $p = 0.01$) significantly predicted PUMR (mean = 25.6, SD = 23.0). The remaining coefficients were not significant. Residual and qqplot plots reveal that no model assumptions were violated (see Supplemental Fig. S2).

Study 3: stability of PUMR across time

The degree of stability of PUMR over time has not previously been studied. If PUMR is primarily influenced by stable environmental risk factors or early childhood experience, it should behave like a trait, remaining stable over repeated measures. In contrast, risk perceptions may rapidly change along with changes in circumstances. Such changes may be especially prevalent during this study window which took place as vaccines were becoming available during the COVID-19 pandemic. During our March survey, only 18.1% of the US population was fully vaccinated (Ritchie et al. 2020). By May, that number had increased to 44.1%, and

in July 51.5% of the US had been fully vaccinated. Here we assess the stability of PUMR using three repeated measures over a 4-month period from March to July.

Measures

Once again, we use the PUMR estimates that participants provided in March 2021 (see Fig. 1 for a timeline of all survey questions). These same participants completed later iterations of the survey 2 months and 4 months later on May 27, 2021, and July 26, 2021. On all these survey dates, participants answered the following question:

> *1. If you made the maximum effort you could make to look after your health and ensure your safety, what do you think the chances would be that you would live to be 79 or more?* (Scale where 0 is "no chance" and 100 is "definitely.")

Estimates of PUMR were again calculated by subtracting these responses from 100.

Analysis

We ran test–retest Pearson correlations between each measurement date. When the distributions were non-normal, we also conducted paired Wilcoxon signed-rank tests in addition to the Pearson correlation analysis.

Results

Responses for PUMR in March (M = 25.6, SD = 23.0), May (M = 24.4, SD = 22.0), and July (M = 25.5, SD = 22.6) were non-normally distributed, positively skewed (see Supplemental Fig. S3). Responses in March are well correlated with responses in May ($R = 0.71$, $p < 0.01$) and July ($R = 0.75$, $p < .01$) and responses in May are also highly correlated with responses in July ($R = 0.78$, $p < .01$). A scatter plot and best fit line for this relationship is presented in Fig. 4. Wilcoxon signed-rank tests show that within-subject responses did not change significantly across these survey dates: March to May ($V = 23{,}896$, $p = 0.28$) and March to July ($V = 20{,}920$, $p = 0.09$).

Study 4: the relationship between PUMR and health/risk-taking behavior

Previous work has found that perceived uncontrollable mortality risk is negatively associated with general health behavior (Pepper and Nettle 2014a; Brown et al. 2021) where individuals who demonstrate high PUMR report taking less care of their health. Here we aim to replicate this result and explore whether PUMR is similarly predictive of a combination of risk-taking behaviors as measured with the DOSPERT [Domain-Specific Risk-Taking] Health/Safety scale (Blais and Weber 2006).

Measures

For this analysis, we use respondents' PUMR estimations from the March iteration of the survey. In October 2021, we asked respondents to answer a question about their general health behavior: "How much effort do you make to look after your health and ensure your safety these days? (0 = No effort at all, 100 = Maximum effort you could)." We assess the relationship between health behavior and PUMR and compare PUMR to scores on the DOSPERT Health/Safety scale. DOSPERT is a six-item questionnaire about participants' likelihood of engaging in various risky behaviors (drinking heavily, engaging in unprotected sex, driving a car without wearing a seatbelt, riding a motorcycle

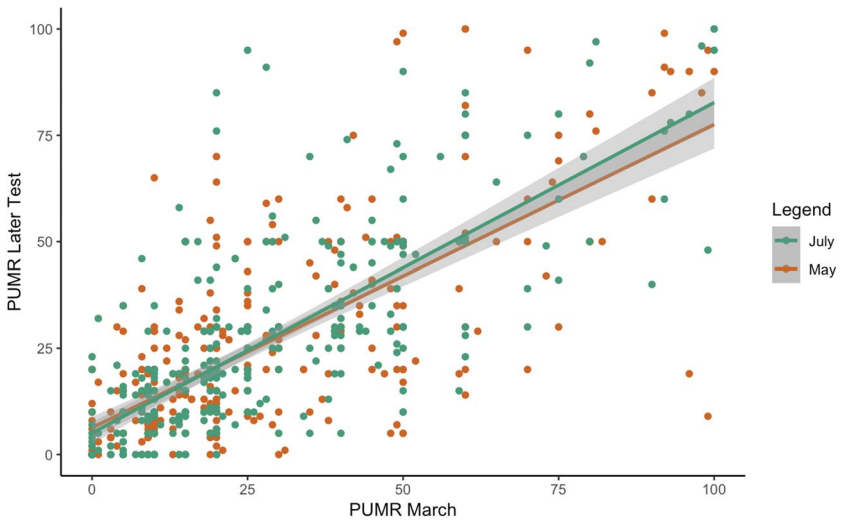

Fig. 4 Scatter plot and best fit line between PUMR measured in March (X axis) and PUMR measured at the later dates: May (Red) and July (Green)

Table 3 Results of OLS regression predicting general health behavior from PUMR, wealth, age, and sex

Variable	β	Std. Error (β)	*t* value	*p*
PUMR	−0.16	0.06	−2.66	0.008
Wealth	0.08	0.07	1.09	0.276
Age	0.08	0.07	1.10	0.273
Education	0.08	0.05	1.64	0.103

Table 4 Results of OLS regression predicting DOSPERT health/risk taking scores from PUMR, wealth, age, and sex

Variable	β	Std. Error (β)	*t* value	*p*
PUMR	0.01	0.05	0.20	0.844
Wealth	−0.11	0.06	−1.94	0.053
Age	−0.22	0.06	−3.84	<0.001
Sex	0.41	0.10	4.19	<0.001

without a helmet, sunbathing without sunscreen, walking home alone at night in an unsafe area of town) answered on a seven-point scale from 1, extremely unlikely, to 7, extremely likely (Blais and Weber 2006). As in the study introducing the scale, responses were summed across questions to arrive at an overall DOSPERT Health/Safety score.

Analysis

We ran an OLS regression model with PUMR as a predictor variable and health behavior as an outcome variable and a separate regression with DOSPERT Health/Safety questionnaire scores as the dependent variable, in both regressions controlling for demographic characteristics that may be associated with differences in perceptions of risk and risk behavior. Before running the regression, all variables were normalized using the *bestNormalize* function.

Results

The results of the OLS regression predicting health behavior (M = 71.9, SD = 22.8), are presented in Table 3 ($R^2 = .07$, $F(4, 241) = 4.37$, $p = .002$). In this case, PUMR was a significant predictor of health behavior, even when controlling for wealth, age, and education, which individually showed significant associations with general health behavior (see Supplemental Table S4 for results with alternative normalization methods scored similarly well by *bestNormalize*).

We ran a similar OLS regression predicting the DOSPERT health risk score (Table 4; $R^2 = .11$, $F(4, 308) = 9.89$, $p < .001$). PUMR did not significantly predict this combined set of risky behaviors. We found that age and sex were significant predictors of these health and risk-taking behaviors (M = 11.4, SD = 6.3) with men and younger individuals being more likely to take risks compared to older and female participants. Additionally, wealth was a negative predictor, with more wealthy respondents less likely to report engaging in the behaviors than participants with less wealth.

General discussion

As hypothesized, we found that PUMR was associated with objective measures of environmental risk based on age, gender, and state. While the relationship was statistically significant, the overall effect size was small, indicating that other, unmeasured, factors may be contributing significantly to these estimates. For example, PUMR may be strongly driven by perceptions of risks from more controllable causes such as chronic diseases (e.g., heart disease) that can be mitigated with proper lifestyle choices. Additionally, we found that perceived risks of death from a number of specific, uncontrollable causes (e.g., disease, air pollution, natural disaster) were well correlated with each other; however, they were only weakly correlated with overall PUMR. These results raise questions about the cognitive mechanisms underlying PUMR estimation. Do individuals employ complex risk-aggregation functions that combine various low-level risks or do they rely on simpler heuristics? Past work has found that the number of close bereavements that a person experiences was associated with less future-oriented behavior including increased financial discounting (i.e., prioritizing smaller-sooner rewards over later-larger ones) and earlier ideal age of a first child (Pepper and Nettle 2013). Close deaths and other types of experiences may be salient cues for informing PUMR, thus motivating these behaviors. Additionally, the social circle heuristic is another mental shortcut people may employ to arrive at risk estimates, where they analyze their social network and probe individuals with various maladies to arrive at their estimates (Pachur et al. 2013).

In the present study, we found that PUMR was relatively stable, with strong test–retest correlations over 2 and 4 months. The strength of this stability is notable given that this longitudinal study took place during the COVID-19 pandemic at a time when vaccines were becoming increasingly available to the public (Ritchie et al. 2020). This stability suggests that PUMR may be driven in part by unchanging environmental characteristics and personal beliefs. Additionally, harsh early life experiences may spark feedback loops that lead

individuals to increase their perceptions of risk in ways that are difficult to change (Pepper and Nettle 2017), so PUMR may be influenced heavily by these early-life experiences and less impacted by later-life experiences. Moving forward, natural experiments (e.g., a natural disaster or social upheavals such as a war or school shooting) may be used to identify features of early or later events that influence PUMR, point to individual differences that mitigate these changes, and indicate how long shifts in PUMR last.

While past work has found robust relationships between PUMR and long-term-oriented health behaviors (e.g., Pepper and Nettle 2014; Brown et al. 2021), which we replicated here with a general health behavior measure, PUMR was not a significant predictor of the health and risk-taking behaviors measured by the DOSPERT scale. Recent work on the items in this scale indicates that they are biased to identify risk-taking behavior in men (Morgenroth et al. 2018), so the specific behaviors we asked about may be more reflective of masculine risk-taking than overall risk or health behaviors. Previous research has also found single-item measures to be more accurate predictors of risky health behaviors than the DOSPERT scale (Szrek et al. 2012). Future work can systematically explore the relationship between PUMR and different health and social behaviors to assess the types of behaviors PUMR is most commonly associated with.

The objective environmental risk SEV measures we used (GBD 2019) come with numerous advantages in that their methodology was rigorous and standardized across locations, and they are also differentiated by age, sex, and location. Still, they are limited in that they are at a state level. This broad spatial dimension leaves room for much heterogeneity within each state, making the data noisier than would be ideal. Future work may use more granular data (e.g., census tract) to account for this limitation. More fine-grained estimates of risk will also empower future efforts to investigate the accuracy of risk perceptions and explore what individual differences may underlie any disparities. For example, Brown et al. found that education was a significant driver of these risk assessments (Brown et al. 2022; Brown et al. 2023). Finally, we used a US-representative sample for this longitudinal study. While such a sample allows us to stake claims about psychology among Americans, it may not generalize to other countries, especially those that are not western or industrialized (Henrich 2020). Future work can use cross-cultural comparisons to assess the replicability and generalizability of these findings.

Throughout this paper, we operationalized risks into binary "controllable" and "uncontrollable" categories, labeling those that the GBD classified as due to environmental/occupational risks as uncontrollable. This distinction, while useful for examining how perceptions of risk map to objective risk exposure, is not without limitations. Most notably, the controllable/uncontrollable split is a false dichotomy, and all risks are somewhat modifiable depending on what an individual is willing to give up to avoid them. Further theoretical and empirical work is necessary to better differentiate between these types of risk and classify them on a continuum. Still, we believe that the overall and cause-specific uncontrollable risk perceptions utilized in this paper provide a fruitful means to test the PUMR hypothesis and assess the relationship between risk perceptions and behavior.

Our findings have potential implications for applied public health. Individuals who overestimate their risk of dying from uncontrollable causes may be biased toward engaging in fewer future-oriented health behaviors, resulting in negative outcomes. By receiving targeted informational interventions, these individuals may lower their inaccurately high PUMR and as a consequence improve their health behavior. In situations where risk perceptions are instead accurate and high, interventions aiming to improve health behaviors and address health inequalities should look beyond perceptual or behavior change strategies to address structural issues as well. Given that objective factors impact perceptions, attempting to nudge the perceptions and behaviors is unlikely to have long-lasting impact until the underlying structural issues are resolved. Little is known about the sources that influence PUMR, so identifying how perceptions of risk from uncontrollable (or controllable) causes are estimated is an important ongoing line of research. By assessing the extent to which objective risk factors influence risk perceptions and how those risk perceptions influence future-oriented behavior, we can better understand the determinants of health behavior and can better minimize social disparities in health outcomes moving forward.

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Availability of data, material, and code All statistical analyses were conducted in R (R Core Team 2021). The R script used for data analysis is available in a public GitHub repository (https://github.com/CalvinIsch/pumr-omr).

Declarations

Ethics approval This study was approved by the internal review board at Arizona State University (HRP-503a). Our predictions, measures, and analysis plan are pre-registered with the Open Science Framework (https://osf.io/wy63d/)

Consent to participate All participants provided informed consent to participate by responding to the following statement: "By continuing and completing the associated survey you certify that you are at least 18 years old, have carefully read this consent form, consent to be contacted through Prolific as a follow up, and agree to participate in this research study. You also understand that you are free to withdraw from this study at any time. No one under the age of 18 is allowed to participate."

Consent for publication Not applicable

Conflicts of interest The authors declare no competing interests.

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