Demographic Predictors of Gas Leak Reporting

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Abstract

Problem Statement

Every year approximately 125,000 natural gas leaks are reported on residential properties across the United States, of which approximately 3.4% progress to fires or explosions. While many researchers have actively sought to identify patterns and behaviors associated with reporting leak occurrence, there remains a dearth of information on the actual determinants of successful leak reporting.

Purpose

Successful gas leak reporting hinges on a variable sequence of actions undertaken by individuals upon suspecting a leak. The purpose of this study is to identify factors that most directly influence residents' predisposition to correctly recognize and ultimately report a gas leak.

Methods

Data from a nationally representative sample (N=598) was analyzed, and responses to questions probing respondents' specific actions upon suspecting a leak were extracted from a larger survey (N=1060). Variables corresponding to respondents' demographics and gas consumption patterns were cleaned, re-coded, and fed into a Poisson regression model. Incident risk ratios were reported for variables associated with an increased number of actions taken upon suspecting a gas leak.

Results

Mean age was 37, with a standard deviation of 12.92. Most individuals were White (74%), and slightly more than half of the sample identified as men (53%). Marital status was almost split in half, with 48% reporting being married or coupled. Approximately 36% reported graduating college while 40% reported a high school education or less. Most respondents reported an income between

$50,000 & $74,999, and a majority were homeowners (62%). Across models, the only two variables that were statistically significant were non-White race and concern for others. (IRR) for non-White race were between 1.215 and 1.226, indicating that non-White individuals were between 22 and 23% more likely to have taken more actions upon suspecting a gas leak. Respondents who reported being concerned for others in the house were between 17 and 20% more likely to take more actions upon suspecting a gas leak (1.166 - 1.199). Specific to model constructs, composite score for perceived thread and information seeking were statistically significant with the former have an IRR of 1.013 [1.003,1.024] and the latter of 0.981 [0.968,0.995].

Discussion

To be added

Keywords: Gas Leak, Health Belief Model, Reporting, Poisson Regression

1. Introduction

Natural gas (NG) is a relatively ubiquitous form of energy across the United States (US), accounting for approximately 34% of the country's total energy consumption and second only to petroleum by source ranking (EIS, n.d.). Several industries rely on NG for their electrical, thermal, chemical, and transportation needs, including the residential sector, which accounts for 15% of total US NG consumption. In effect, the US Energy Information System estimates that half of all homes use NG for household needs including space heating, water heating, cooking, washing, and drying.

Along with this versatility, however, NG usage exposes a significant portion of the population to a potentially deadly gas leaks. Approximately 125,000 leaks are reported on residential properties across the US every year (Ahrens & Evarts, 2018), with most caused by inadequate maintenance of aged distribution systems, resulting in corrosion and other structural defects, as well as a diminished capacity to handle gas pressure (Keyes et al., 2020).

Classic signs and symptoms of an active leak may involve olfactory, visual, and auditory cues, including a pungent sulfur odor, dying vegetation, and hissing, gurgling, or roaring sounds near faulty pipelines (Leonard, 2018). Other signs may include dirt and debris in the air, or a strong, distinct smell like rotten eggs.

This study expands on the work of Dr. Nicholas Grosskopf, a professor in the School of Health Sciences & Professional Programs at York College. He investigated behavioral responses to detecting and reporting a leak using established health behavior theories such as the Health Belief Model and the Theory of Planned Behavior. He surveyed a nationally representative sample of 1,044 individuals online using various measures exploring constructs such as perceived threat of a leak, perceived benefits of reporting a leak, and perceived barriers to reporting a leak (Grosskopf, 2021).

2. The Health Belief Model

2.1 Background

Noticing the population failed to follow preventative measures for early detection of disease, despite relative ease of access Rosenstock (1974) developed the Health Belief Model (HBM). While the first iteration of the HBM was primarily created to ascertain beliefs and behavior towards disease prevention and early detection measures, the scope of the model was extended to include response to diagnosed illness and medication adherence (Becker, 1974).

2.2 Structure

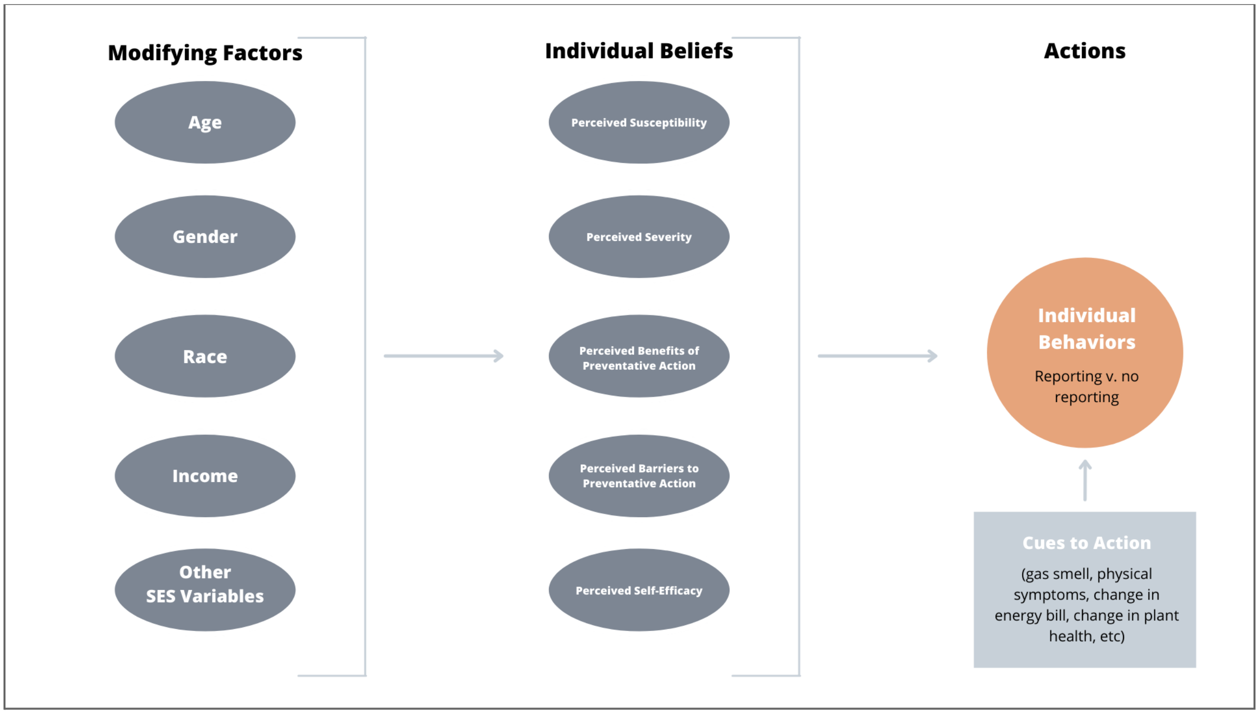
The HBM incorporates elements from the Stimulus Response Theory (Watson, 1925) and Cognitive Theory. The former stipulates that behavior is directly reinforced by its immediate consequences (Skinner, 1938), while the latter introduces the influence of a third factor, the subjective interpretation of the consequential events (Lewin, 1951). Cognitive theorists believed behavior was informed by one's interpretation of the resulting developments, as opposed events themselves. The model itself includes conceptual predictors of preventive action and adequate symptom management. These constructs include: *perceived susceptibility*, which refers to one's belief about his/her likelihood of acquiring a disease or condition;*perceived severity*, which explores one's feeling towards the severity of the effects of a disease;*perceived benefits*, which further influences one's perceived susceptibility through belief in the relative benefits of adopting recommended behaviors; *perceived barriers*, which are considered to be impediments to one's ability to take preventive actions; cues to action, which generally include nonspecific triggers that may prompt action; and *self-efficacy*, which is defined as one's belief in one's ability to successfully take recommended courses of action towards a desired outcome. A group of *modifying factors* is also included in the model to account for the potential influence of demographic and socioeconomic elements such as gender, ethnicity, and income (Figure 1).

2.3 Performance

A longitudinal review of the application of the HBM in various studies between 1974 and 1984 found extensive empirical support for its efficacy (Becker, 1974; Janz & Becker, 1984). Individual constructs have been further assessed over the years through context-specific validated scales, including breast cancer (Champion, 1984; 1993; 1999). A more recent study on the determinants of breast self-examination performance among Iranian women found support for the usefulness of the HBM in identifying factors influencing BSE adoption (Noroozi et al., 2010). Darvishpour's report, (2018) demonstrated that perceived benefits, self-efficacy, and perceived barriers collectively predicted breast self-examination among North Iranian women. Perceived benefits and perceived barriers were found to predict adherence to screenings such as mammography.

The HBM has also been used to assess preventive behaviors across several public health topics, exercise (Wu et al., 2020), cardiovascular disease (Lim et al., 2021), and COVID-19 (Karl et al., 2022). Karl's study demonstrated that perceived barriers, perceived benefits, and self-efficacy were strong predictors of COVID-19 preventive health behaviors, which is consistent with other findings from the literature (Shanazi et al., 2020; Karimy et al., 2021; Alagili & Bamashmous, 2021).

Figure 1: Health Belief Model



3. Gas Leak Literature

The importance of residential early leak detection has been periodically referenced in the literature. A 2019 review by Dorothy Stearns and Kanta Sircar explored the prevalence of unintentional non fire-related carbon monoxide poisoning through Emergency Department data. Using the National Inpatient Sample database (NIS) and the National Emergency Department Sample (NEDS), Stearns and Sircar assessed 2013-2017 CO-related ED visits and hospitalizations and ascertained possible longitudinal trends. They analyzed over 100,000 ED visits related to confirmed or probable CO poisoning, with cases further stratified by age, race, gender, and location. Mortality rates were also calculated for each database sample. Importantly, their findings demonstrated that most cases of non-fire-related CO poisoning occur in residences, caused by sources including stoves, charcoal grills, kerosene heaters, and generators (Stearns & Sircar, 2019).

The implications of source quality in leak frequency have also been addressed by researchers

Marty Ahrens and Ben Evarts in a 2018 study summarizing detailed findings from the National Fire Protection Association (NFPA), which tracks residential gas leak prevalence, residential fires and explosions caused by gas leaks, as well as financial burdens associated with unaddressed leaks. According to the report, cooking, and heating equipment, such as stoves and space heaters, were probable causal factors in approximately 90% of fires & explosions. Aged materials were also identified as risk factors in approximately 27% of fires (Ahrens & Evarts, 2018).

The impact of poor material quality on leak prevalence is additionally explored by Zachary Weller, Steven Hamburg, and Joseph von Fischer in a 2020 statistical analysis of national methane leakage. Weller and colleagues used data collected from an advanced mobile leak detection platform (AMLD) to approximate the total annual number of gas leaks across the US. Their model estimates that approximately 630,000 gas leaks occur across US distribution mains, while also identifying a clear negative correlation between pipeline quality and age, with older pipelines demonstrating an increased propensity for leaks (Weller et al., 2020). These findings have far-reaching implications for several households using aged kitchen utensils, as cooking is also believed to produce 20 to 100 times more Nitrous Oxide (NO), Nitrogen Dioxide (NO_2), and Nitrous Acid (HONO) than baseline indoors and outdoors background levels (Zhou et al., 2018).

A meta-analysis of findings from 19 studies on the association between gas stoves and asthma demonstrated increased odds of developing both acute and chronic asthma symptoms upon gas exposure (Lin et al., 2013). Indoor Nitrogen Dioxide exposure increased asthma likelihood by 15%, while overall odds ratio for all gasses was 1.32.

4. Methods

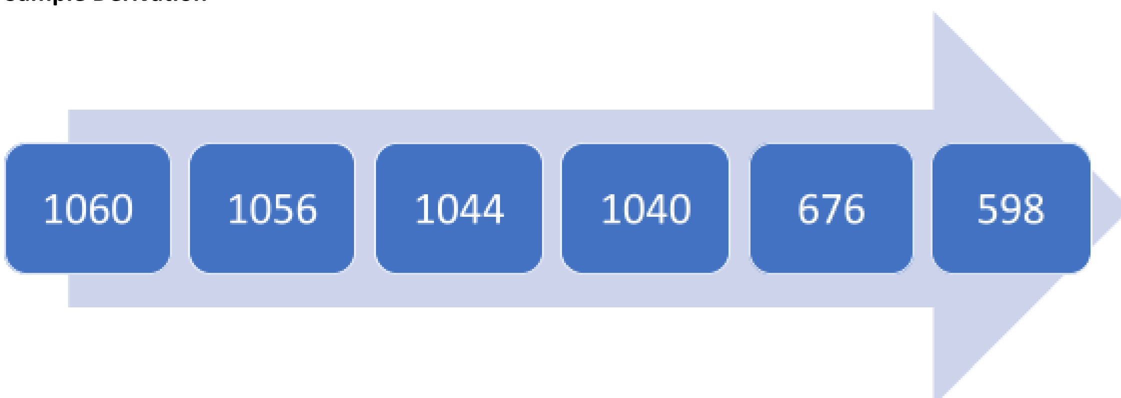
4.1 Data

The data were collected from an instrument created for a previous study. Records were dropped if the respondent did not receive gas (N=4), had incomplete data (N=94), did not suspect having a gas leak (N=364), or did nothing upon suspecting a gas leak. Figure 1 shows the sample derivation.

4.2 Sample

Initially the file had 1060 records. Four individuals did not receive gas. Fourteen didn't answer if they received gas. An additional 364 did not suspect a gas leak and another four did not answer this question. Finally, 78 did not answer questions necessary for the analysis.

Figure 1: Sample Derivation



4.3 Independent Variables

Variables were extracted from the larger survey, including demographic variables, and those with few records were re-coded. For example, race was dichotomized to White versus non-White because some categories had too few records. Marital status was also dichotomized. Some levels, such as education and employment status, were collapsed into fewer categories. Individuals who identified as transgender women (N=2) were recoded as women, and the same was done for transgender men who were coded as men. Family or household size was addressed through a variable probing the respondent's motivation to report a gas leak. Specifically, this was achieved with a question assessing the individual's degree of concern for others in the home. Finally, composite scores for Health Belief Model constructs were used to determine whether they predicted the outcome.

4.4 Dependent Variable

The dependent variable was the count of actions taken as a response to suspecting a gas leak. This variable was created by summing the number of actions the respondent reported. These included things such as calling 911 and vacating the home.

4.5 Reference Categories for Predictor Variables

The reference category for a variable is the value against which all other values of the variable are compared to when explaining the model outcomes. In order of variable placement in the model, the first reference was the answer to whether the respondent suspected the gas leak, and the answer was "yes". Therefore, the response *doubts gas leak* is compared to results for *had gas leak*. For gender, the reference was *men*, and for marital status it was *single*. Education and employment status had three levels. For the former, the reference category was *less than high school* and for the latter, the reference was *employed full time*. For race, the reference was *White*, and for income, it was *less than $15,000*. The reference for home ownership status was *owner*, and for care for others was *not caring for others*. Reference categories are not displayed in the regression table or accompanying graph.

4.6 Continuous Predictor Variables

Age was a continuous variable. The other continuous variables were the composite Health Belief Model scores – perceived threat, perceived benefit, perceived barriers, cues to action, and information seeking.

4.7 Analysis

All analysis was done using STATA version18. Descriptive statistics were run on all variables to create table 1. Since the outcome was a count, a Poisson regression was used to analyze the relationship between the predictor variables and the number of actions taken. A Poisson regression is appropriate when the outcome variable is neither continuous nor binary. The models were given the IRR command, which yields the incidence rate ratio instead of the coefficient. An IRR value greater than 1 indicates a greater likelihood compared to the reference value. The *eststo* and *esttab* functions were used to create the output tables, which were formatted to Microsoft WORD. The *coefplot* function was used to create forest plots.

5. Results

5.1 Descriptive Statistics

The final sample was 598, 71% of which reported being certain that they had a gas leak. The mean age was 37, with a standard deviation of 12.92. Slightly more than half of those surveyed were men (53%). Marital status was almost split in half, with 48% reported being married (or coupled). Approximately 36% reported graduating college, but 40% reported having a high school education or less. The remainder had at least some graduate school education. Seventy-four percent of respondents were white. Income groups were widely distributed, with most respondents making between $50,000 and $74,999. Sixty-two percent of the sample were homeowners. Mean scores for the Health Belief Model composite scores are reported in Table 1.

Table 1: Variables

Variable		N(%)	Avg. (SD)
	Suspected Gas Leak	427 (71.40%)	
Gender	Men	317 (53.01)	
	Women	281 (46.91)	
Age			37(12.97)
Marital Status	Married	288 (48.16)	
	Single	310 (51.84)	
Level of Education	College	214 (35.79)	
	Graduate School	144 (24.08)	
	High School or Less	240 (40.13)	
Employment Status	Employed	444 (40.13)	
	Student	57 (9.53)	
	Unemployed	97 (16.22)	
Race	White	445 (74.41)	
	Non-White	153 (25.59)	
Income	Less than $15,000	88 (14.72)	
	$15,000-$34,999	104 (17.39)	

Variable		N(%)	Avg. (SD)
	$35,000-$49,999	78 (13.04)	
	$50,000-$74,999	119 (19.9)	
	$75,000-$99,999	95 (15.89)	
	$100,000-$124,999	34 (5.69)	
	$125,000-$149,000	38 (6.35)	
	$150,000 and above	42 (7.02)	
Homeowner Status	Homeowner	371(62.04)	
	Renter	227(37.96)	
Health Belief Model Constructs	Threat		39.8(6.45)
	Benefit		37.05(5.99)
	Barrier		29.53(10.08)
	Cue to Action		87.43(15.4)
	Info Seek		14.06(4.83)

5.2 Regression Models

Models were run for each of the Health Belief Model (HBM) constructs. Across models, the only non-HBM variables that predicted the number of actions a respondent took upon suspecting a residential gas leak were non-White race and care for others. This is apparent in Figure 1, where these variables do not cross the vertical axis representing 1. If the confidence intervals do not include 1, the results are statistically different from 1 and therefore statistically significant. The incident risk ratios for both variables were greater than 1, indicating these two variables predicted a respondent did more (took more actions) in response to the gas leak.

For non-White race, the IRR were between 1.215 and 1.226. In other words, compared to the White sample, non-White individuals were between 22 and 23% more likely to have taken more actions on suspecting a gas leak.

The variable *concern for others* had IRR's between 1.166 and 1.199. This means that respondents who reported being concerned for others in the house were between 17 and 20% more likely to take more actions on suspecting a gas leak.

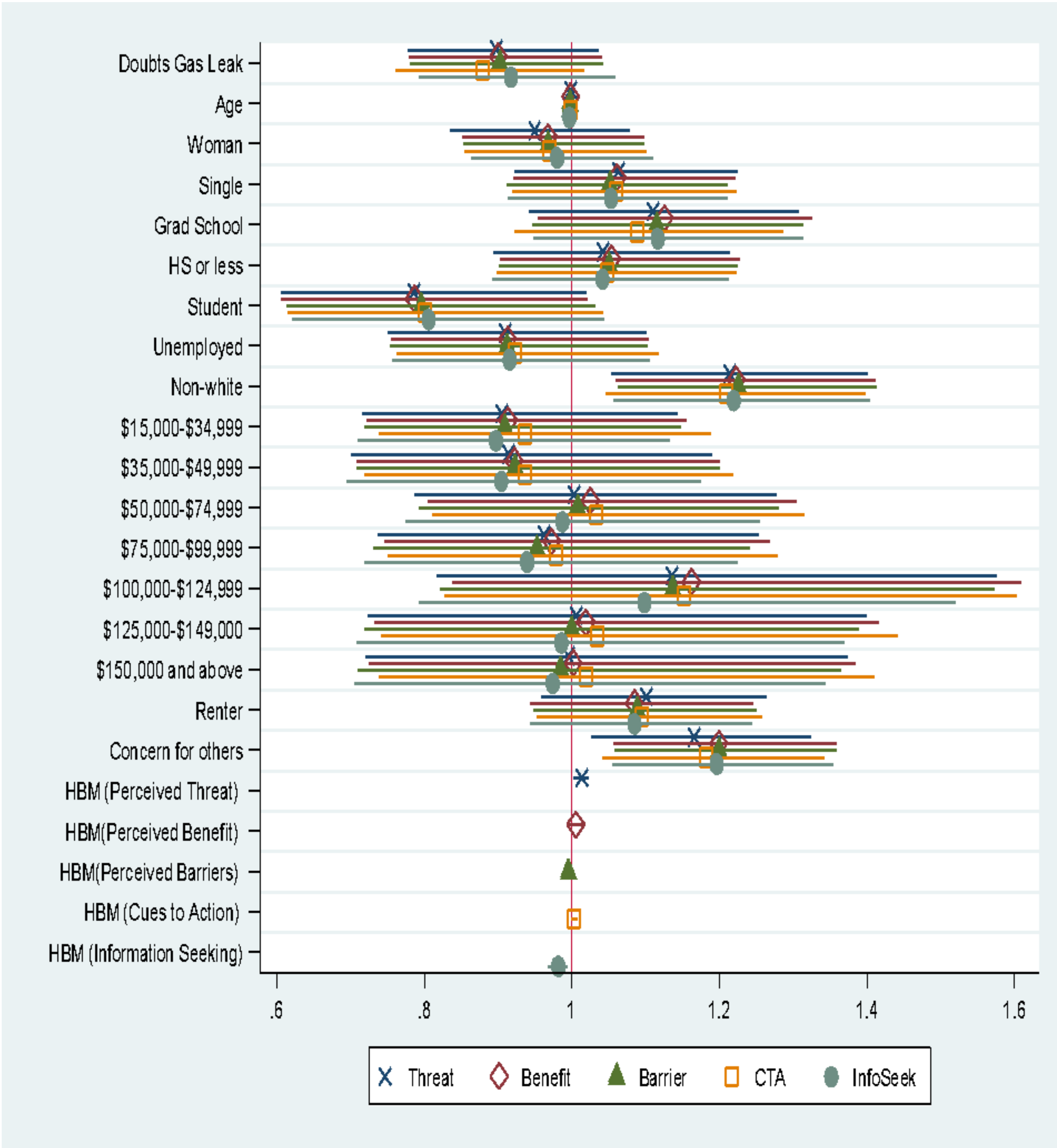
Specific to each Health Belief Model construct, all incident risk ratios had narrow confidence intervals (Figure 1). The perceived threat was significant at p.<0.05 and seeking information was significant at p<0.001. The latter had an IRR of .981. Since these measures are continuous variables, they are interpreted differently.

The rate ratio is estimated for a one unit increase in the measure, provided that the other variables in the model are held constant. If an individual were to increase his score for Health Belief Model threat, his number of actions taken (the outcome, or Y variable) would be expected to increase by a factor of .02. If an individual were to increase his*information seek* score, the outcome variable, number of actions taken on suspecting a gas leak, would decrease by a factor of 0.981.

Table 2: Poisson Results

Variable	**Threat**	Benefit	Barrier	Cue to Action	Info Seek
Doubts Gas Leak	0.898	0.901	0.902	0.88	0.917
	[0.778,1.038]	[0.779,1.041]	[0.781,1.043]	[0.761,1.017]	[0.793,1.060]
Age	0.999	0.998	0.997	0.999	0.996
	[0.993,1.004]	[0.993,1.004]	[0.991,1.003]	[0.993,1.005]	[0.990,1.002]
Women	0.95	0.968	0.968	0.97	0.98
	[0.836,1.079]	[0.852,1.100]	[0.853,1.098]	[0.854,1.102]	[0.863,1.112]
Single	1.064	1.061	1.052	1.061	1.053
	[0.923,1.225]	[0.921,1.223]	[0.912,1.213]	[0.919,1.224]	[0.914,1.212]
Graduate School	1.11	1.126	1.115	1.09	1.116
	[0.942,1.309]	[0.955,1.327]	[0.946,1.314]	[0.923,1.287]	[0.948,1.315]
High School	1.042	1.054	1.051	1.049	1.041
	[0.894,1.215]	[0.904,1.229]	[0.901,1.225]	[0.899,1.224]	[0.893,1.214]
Student	0.786	0.787	0.796	0.801	0.805
	[0.606,1.021]	[0.606,1.022]	[0.614,1.032]	[0.615,1.043]	[0.621,1.044]
Unemployed	0.91	0.913	0.912	0.924	0.915
	[0.751,1.102]	[0.754,1.105]	[0.754,1.103]	[0.762,1.119]	[0.757,1.107]
Nonwhite	1.215^{**}	1.223^{**}	1.226^{**}	1.210^{*}	1.219^{**}
	[1.053,1.402]	[1.060,1.412]	[1.063,1.414]	[1.047,1.399]	[1.057,1.406]
$15,000-$34,999	0.906	0.913	0.909	0.937	0.897

	[0.717,1.145]	[0.722,1.156]	[0.719,1.149]	[0.738,1.189]	[0.709,1.133]
$35,000-$49,999	0.914	0.922	0.923	0.937	0.904
	[0.701,1.191]	[0.708,1.202]	[0.709,1.202]	[0.719,1.220]	[0.694,1.177]
$50,000-$74,999	1.004	1.025	1.008	1.034	0.987
	[0.788,1.279]	[0.806,1.305]	[0.792,1.282]	[0.811,1.317]	[0.775,1.256]
$75,000-$99,999	0.962	0.973	0.953	0.98	0.939
	[0.737,1.255]	[0.746,1.270]	[0.730,1.243]	[0.750,1.280]	[0.720,1.225]
$100,000-$124,999	1.135	1.162	1.137	1.152	1.098
	[0.817,1.577]	[0.839,1.611]	[0.822,1.573]	[0.828,1.604]	[0.793,1.521]
$125,000-$149,000	1.007	1.019	1	1.034	0.985
	[0.724,1.401]	[0.733,1.417]	[0.719,1.390]	[0.741,1.443]	[0.708,1.371]
$150,000 and above	0.996	1.002	0.985	1.021	0.974
	[0.721,1.375]	[0.725,1.385]	[0.711,1.365]	[0.738,1.411]	[0.705,1.344]
Renter	1.101	1.085	1.089	1.096	1.085
	[0.958,1.265]	[0.944,1.247]	[0.948,1.251]	[0.953,1.259]	[0.944,1.246]
Concern for Others	1.166*	1.199**	1.199**	1.183**	1.196**
	[1.026,1.326]	[1.057,1.360]	[1.058,1.360]	[1.042,1.343]	[1.055,1.356]
HBM Threat	1.013*				
	[1.003,1.024]				
HBM Benefit		1.006			
		[0.995,1.016]			
HBM Barrier			0.995		
			[0.989,1.002]		
HBM CTA				1.004	
				[1.000,1.008]	
HBM Info Seek					0.981**
					[0.968,0.995]
N	**594**	592	593	585	598



Discussion

To be added

Appendix

STATA Code for Models, Data output to WORD and Multiple Model Forest Plots

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eststo: poisson numresp i.gasleak_suspicion age_continuous i.gender_combined i.M_stats i.EdLevel i.EmploymentS i.race_dichotomous i.Income i.OwnHome i.CareforOthers hbm_per_thrt_composite , irr
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References

1. Wu, S., Feng, X., & Sun, X. (2020). Development and evaluation of the health belief model scale for exercise. International journal of nursing sciences, 7(Suppl 1), S23–S30. https://doi.org/10.1016/j.ijnss.2020.07.006

2. Darvishpour, A., Vajari, S. M., & Noroozi, S. (2018). Can Health Belief Model Predict Breast Cancer Screening Behaviors?. Open access Macedonian journal of medical sciences, 6(5), 949–953. https://doi.org/10.3889/oamjms.2018.183

3. He, Z., Feng, J., Xia, J., Wu, Q., Yang, H., & Ma, Q. (2020). Frequency of Signs and Symptoms in Persons With Asthma. Respiratory care, 65(2), 252–264. https://doi.org/10.4187/respcare.06714

4. Alagili, D. E., & Bamashmous, M. (2021). The Health Belief Model as an explanatory framework for COVID-19 prevention practices. Journal of infection and public health, 14(10), 1398–1403. https://doi.org/10.1016/j.jiph.2021.08.024

5. Shahnazi, H., Ahmadi-Livani, M., Pahlavanzadeh, B., Rajabi, A., Hamrah, M. S., & Charkazi, A. (2020). Assessing preventive health behaviors from COVID-19: a cross sectional study with health belief model in Golestan Province, Northern of Iran. Infectious diseases of poverty, 9(1), 157. https://doi.org/10.1186/s40249-020-00776-2

6. Lim, B. C., Kueh, Y. C., Arifin, W. N., & Ng, K. H. (2021). Modeling knowledge, health beliefs, and health-promoting behaviors related to cardiovascular disease prevention among Malaysian university students. PloS one, 16(4), e0250627. https://doi.org/10.1371/journal.pone.0250627

7. Karimy, M., Bastami, F., Sharifat, R., Heydarabadi, A. B., Hatamzadeh, N., Pakpour, A. H., Cheraghian, B., Zamani-Alavijeh, F., Jasemzadeh, M., & Araban, M. (2021). Factors related to preventive COVID-19 behaviors using health belief model among general population: a cross sectional study in Iran. BMC public health, 21(1), 1934. https://doi.org/10.1186/s12889-021-11983-3

8. Karl, J. A., Fischer, R., Druică, E., Musso, F., & Stan, A. (2022). Testing the Effectiveness of the Health Belief Model in Predicting Preventive Behavior During the COVID-19 Pandemic: The Case of Romania and Italy. Frontiers in psychology, 12, 627575. https://doi.org/10.3389/fpsyg.2021.627575

9. Shan Zhou, Cora J. Young, Trevor C. VandenBoer, Shawn F. Kowal, and Tara F. Kahan. Environmental Science & Technology 2018 52 (15), 8355-8364. https://doi.org/10.1021/acs.est.8b01792

10. Weiwei Lin, Bert Brunekreef, Ulrike Gehring, Meta-analysis of the effects of indoor nitrogen dioxide and gas cooking on asthma and wheeze in children, International Journal of Epidemiology, Volume 42, Issue 6, December 2013, Pages 1724–1737, https://doi.org/10.1093/ije/dyt150

11. Stearns, D., & Sircar, K. (2019). National unintentional carbon monoxide poisoning estimates using hospitalization and emergency department data. The American journal of emergency medicine,

37(3), 421–426. https://doi.org/10.1016/j.ajem.2018.06.002

12. Luna M., Nicholas D. (2022). An environmental justice analysis of distribution-level natural gas leaks in Massachusetts, USA. Energy Policy, Volume 162, 2022. 112778, ISSN 0301-4215. https://doi.org/10.1016/j.enpol.2022.112778.

13. Weller Z., Hamburg S., Von Fischer J. (2020). A National Estimate of Methane Leakage from Pipeline Mains in Natural Gas Local Distribution Systems. Environmental Science & Technology 2020. 54 (14), 8958-8967 https://doi.org/10.1021/acs.est.0c00437

14. Ahrens M., Evarts B. (2018). Natural Gas And Propane Fires, Explosions And Leaks Estimates And Incident Descriptions. National Fire Protection Association. Retrieved from https://www.nfpa.org/-/media/Files/News-and-Research/Fire-statistics-and-reports/Hazardous materials/osNaturalGasPropaneFires.ashx on March 22, 2022

15. Grosskopf, N. (2021). Exploring Human Behavioral Responses to Detecting and Reporting Natural Gas Odors in New York City:A Mixed-and Multi-Method, Community-Based Study. National Fire Protection Association. Retrieved from https://www.nfpa.org/-/media/Files/News and-Research/Fire-statistics-and-reports/Hazardous-materials/osNaturalGasPropaneFires.ashx on March 22, 2022

16. Rachlin, H. (2018). Skinner (1938) and Skinner (1945). *Behavior and Philosophy*, *46*, 100–113. https://www.jstor.org/stable/26626606

17. Lewin, K (1951) Field Theory in Social Science: Selected Theoretical Papers (ed. Cartwright, D). New York: Harper & Row.

18. John B. Watson (1925) Experimental Studies on the Growth of the Emotions, The Pedagogical Seminary and Journal of Genetic Psychology, 32:2, 328-348, https://doi.org/10.1080/08856559.1925.10534071