Ability, Integrity, and Benevolence: Re-examining Predictors of Trust for Scientists (Analysis)

DANIEL LEEDS

Table of Contents

Analysis *3*

Analysis Plan 3

Code 4

Data 4

Questions And Questionnaire Selection 5

Data preparation 11

Computational Reproducibility 14

Preliminary Analysis 14

Main Analysis: Tests of theory 17

Analysis

Analysis Plan

The broad objective for the following analysis was to examine perceptions of trustworthiness as predictors of public trust in scientific experts, with a particular focus on those which can be readily related to established theories of trust, such as the Integrative Model of Organizational Trust (Mayer et al.,1995). Specifically, this analysis intended to focus on trustworthiness perceptions which fit within the categories of ability, integrity, and benevolence. Part of the original aim for the analysis was to replicate a statistical method employed in a previous study by Eiser et al., (2009), using data from a large-scale split ballot survey conducted by the Pew Research Center (2019). Initial inspections of the survey made it clear that a full replication would not be feasible with the available data. The data did not contain precise analogues of the variables used by Eiser et al., (2009). Instead, a decision was made to select questions from the survey which could serve as the best available fit to the theoretical concepts being investigated, and could be mapped to questions originally used as measures by Eiser et al., (2009). This process helped to identify that the target dependent variable (confidence in scientists) was only available for perceptions of one of the three types of scientists included in the survey. Therefore, confidence in scientists is examined for one group only, "medical scientists" with the intent to compare the overall pattern of effect sizes of predictors with those found for independent scientists in Eiser et al., (2009). The remaining selected variables were available for all three groups. Three measures of integrity were identified and termed appropriately (openness, communication bias, responsibility), one measure of benevolence (shared values), and one measure of ability (competence). Data from these measures was inspected and analysed using a multiple linear regression. However, it should be noted that the data did not entirely suit this form of analysis. The data was ordinal in nature and may have benefitted from statistical tests for this data type, such as ordinal regression. Additionally, not all the assumptions for linear regression were ideally met. Nevertheless, to conduct this analysis as a replication, it was decided to continue with multiple linear regression, while noting the potential drawbacks of this choice.

Code

The entire data processing and analysis for this study was conducted using R version 4.2.2 running on MacOS Monterey version 12.6.3. The full code and materials for this project are shared via a private Google drive (Google drive link) and a public GitHub repository (repo link). The license of the data used for this project does not permit public sharing, and so the GitHub repository linked within this document does not contain the raw data files, but instead contains a link to where data can be requested, all other materials and code are present within this GitHub repository. A license for all code in this project is provided and is the MIT license.

Data

The data for this project came from the Pew Research Centre's American Trends Panel (ATP) Wave 42 split-ballot survey (Funk et al., 2019). The Pew Research Centre is an internationally recognised research organisation that conducts surveys on various public issues. The American Trends Panel is an online panel designed to be nationally representative to the United States of America (US). Prior to Wave 42, ATP panellists were recruited over various periods between January 2014 to October 2018 via three random-digit-dial (RDD) phone surveys, and one national address-based sample (ABS) survey. The survey for wave 42 was conducted from January 7 to January 21, 2019, and successfully garnered responses from had 4,464 participants, inclusive of both English and Spanish speakers. The primary target population for Wave 42 encompassed individuals aged 18 and above, residing within the US.

The sample was subsequently stratified based on demographic under-representation, and the collected data was weighted to support reliable inference from the panel to the target population of US adults. The survey data encompasses a range of measures assessing perceptions of various professions, including scientists. However, given the split-ballot design of the survey, only approximately half of the respondents (n=2226) were presented with the specific questions examining perceptions of scientists used for the current analysis. These questions included an overarching confidence metric for medical scientists and delineated five distinct measures representing various facets of trustworthiness across three scientist categories, including medical research scientists, environmental research scientists, and nutrition research scientists. Pertinent to the purpose of the current study, the survey included five individual questions that resonated with trustworthiness perceptions and mapped to some extent with the trust predictors employed by Eiser et al. (2009). A constraint within this dataset was the exclusive focus of the confidence measure on medical scientists, despite other measures encompassing all three types of scientists. This meant the most direct measure of trust within this dataset was not available for analysis across all three scientist groups, thus preventing comparison.

Full reference for data: Pew Research Center. (2019, August 2). *American trends panel wave 42 archives*. Pew Research Center Science & Society. https://www.pewresearch.org/science/dataset/american-trends-panel-wave-42/

Questions And Questionnaire Selection

The survey covered a wide range of topics related to public attitudes toward science. Notably, the survey was designed as a split-ballot, containing two distinct questionnaires. An examination of the combined questionnaire was undertaken to identify questions for their relevance to specifically assessing trust in science, potential to represent dimensions of trust or trustworthiness established in the literature, and whether they could be reasonably aligned with the questions employed and concepts examined by Eiser et al., (2009). This process revealed six questions which matched all criteria and were suitable for the intended analysis of the current study. All six of these questions were located within one of the questionnaires within the survey (form 1).

The current analysis focused on this subset of survey questions, these six questions were interpreted as providing a measure for overall trust, and three specific dimensions of trustworthiness: ability, integrity, and benevolence. These questions specifically targeted perceptions of three distinct types of scientists: medical research scientists, environmental research scientists, and nutrition research scientists. The survey did not explicitly contain any direct measures of trust.

All selected questions were assessed using a 1-4 Likert scale, with the four response categories being "a great deal of confidence (1)", “a fair amount of confidence (2)” “not too much confidence (3)”, "no confidence at all (4)". Responses on this item were subsequently transformed so that higher values indicated more positive perceptions.

Confidence

Overall confidence in scientists was measured with a single question. Only responses to this question in relation to perceptions of “medical scientists” were collected in the survey and were available for the current analysis. This item was interpreted as the best available measure to gain insight into participants overall trust in medical scientists, and was included as a dependent variable to test hypothesis H1- H4. The specific wording for this question was “how much confidence, if any, do you have in each of the following to act in the best interests of the public?”. Descriptive statistics for this measure can be viewed in Table 1.

Competence (Ability)

Competence was measured with 3 questions, with each using the same wording and response categories but relating specifically to only one of the scientist groups. Were this question was asked in relation to medical research scientists it was included as a predictor variable for hypothesis H1-H4, and a dependent variable for hypothesis H5 and H6. Participants were asked to rate how often each type of scientist "does a good job conducting research". This question was mapped to the measure of expertise employed by Eiser et al., (2009), which asked "If there was CONTAMINATED land in your neighbourhood how able do you think each of the following would be to judge how safe or dangerous it was? The specific wording of the questions employed in the current analysis was "thinking about 'scientist group' how often would you say they do a good job conducting research?". For descriptive statistics see Tables 1-3.

Shared Values (Benevolence)

Shared values were measured via 3 questions, with each question using the same wording and response categories but relating specifically to only one of the scientist groups. Participants were asked to rate how often they believe each type of scientist " Care about the best interests of the public ". These questions were included as a predictor variable for all six listed hypotheses. The questions were selected for alignment to the measure of shared values employed by Eiser et al., (2009), which asked "How much do you think each of the following have your own interests at heart?". The specific wording of the questions used for the current analysis was "Thinking about 'scientist group' how often would you say they care about the best interests of the public". For descriptive statistics see Tables 1-3

Openness (Integrity)

Openness was measured with 3 questions, each question using the same wording and response categories but relating specifically to only one of the scientist groups. These questions were included as predictor variables for all six hypothesise. Participants were asked to rate how often each type of scientist "are transparent about potential conflicts of interest with industry groups in their research?". These questions were selected to align with the measure of openness employed by Eiser et al., (2009), which asked ""how prepared do you believe each of the following would be to tell you what they know about risks from contaminated land?" The specific wording of the questions used for the current analysis was "Thinking about "scientist group" how often would you say they are transparent about potential conflicts of interest with industry groups in their research?". For descriptive statistics see Tables 1-3.

Communication bias (Integrity)

Communication bias was measured with three questions, each using the same wording and response categories but relating specifically to only one of the scientist groups. These questions were included as predictor variables for all six hypotheses, and aligned to the measure of communication bias employed by Eiser et al., (2009). Participants were asked to rate how often each type of scientist "provide fair and accurate information". This question was mapped to the question employed by Eiser et al., (2009), which asked "Do you believe each of the following would tend to underplay or exaggerate the risks from contaminated land when communicating to the public?". The specific wording of the question used for the current analysis was "Thinking about "scientist group" how often would you say they provide fair and accurate information when making statements about their research?". For descriptive statistics see Tables 1-3.

Responsibility (Integrity)

Responsibility was measured with 3 questions, each using the same wording and response categories but relating specifically to only one of the scientist groups. These questions were included as predictors for all six hypotheses, and as a further measure of integrity. Participants were asked to rate how often they believed each type of scientist would "admit mistakes and take responsibility for them". It was decided that this question was most aligned to the measure of trust employed by Eiser et al., (2009), which asked “how much would you trust what each of the following might tell you about risks from contaminated land?” However, the specific wording of the question used for the current analysis was considered to be better represented as a measure of integrity and labelled as responsibility. The precise wording of these questions were “thinking about ‘scientist group’ how often would you say they admit mistakes and take responsibility for them?”. For descriptive statistics see Tables 1-3.

Table 1. Descriptive Statistics for Medical Research Scientists Subset of Pew 2019 Trust and Trustworthiness Data.

Medical research scientists Subset (*n* = 2172)

	Mean	Median	Mode	*SD*	Min	Max	Range	Skewness	Kurtosis
Confidence (*Trust)*	3.24	3	3	0.68	1	4	3	-0.62	3.35
Competence (*Expertise*)	3.37	3	3	0.65	1	4	3	-0.73	3.44
Shared Values	3.21	3	3	0.75	1	4	3	-0.71	3.22
Communication Bias (*Integrity*)	3.20	3	3	0.68	1	4	3	-0.56	3.28
Responsibility (*Integrity*)	2.72	3	3	0.79	1	4	3	-0.33	2.77
Openness (*Integrity*)	2.76	3	3	0.77	1	4	3	-0.34	2.86

Table 2. Descriptive Statistics for Environmental Research Scientists Subset of Pew 2019 Trust and Trustworthiness Data.

Environmental research scientists Subset (*n* = 2159)

	Mean	Median	Mode	*SD*	Min	Max	Range	Skewness	Kurtosis
Competence (*Expertise*)	3.30	3	3	0.72	1	4	3	-0.84	3.54
Shared Values	3.19	3	3	3.19	1	4	3	-0.77	3.14
Communication Bias (*Integrity*)	3.17	3	3	0.68	1	4	3	-0.63	2.97
Responsibility (*Integrity*)	2.75	3	3	0.83	1	4	3	-0.36	2.65
Openness (*Integrity*)	2.83	3	3	2.83	1	4	3	-0.41	2.82

Table 3. Descriptive Statistics for Nutrition Research Scientists Subset of Pew 2019 Trust and Trustworthiness Data.

Nutrition research scientists Subset (*n* = 2142)

	Mean	Median	Mode	*SD*	Min	Max	Range	Skewness	Kurtosis
Competence (*Expertise*)	3.16	3	3	0.68	1	4	-0.61	3.62	3.16
Shared Values	3.05	3	3	0.72	1	4	-0.52	3.32	3.05
Communication Bias (*Integrity*)	2.63	3	3	0.80	1	4	-0.28	2.67	2.63
Responsibility (*Integrity*)	2.68	3	3	0.79	1	4	-0.36	2.80	2.68
Openness (*Integrity*)	3.12	3	3	0.77	1	4	-0.72	3.41	3.12

Data preparation

Package Installation and Library Loading:

- Essential packages - haven, dplyr, ggplot2, car, purrr, moments, viridis, gridExtra, purr, broom, grid, coefplot, and corrplot were installed and subsequently loaded to facilitate data manipulation, visualization, and analysis.

Data Importation:

- Raw data file imported from the SPSS file "ATP W42.sav" using the read_spss() function from the haven package.
- Working directory was set using the setwd function to ensure seamless data access.

Data Cleaning:

- The dataset used '99' as a code to represent respondents who "refused to answer", so these values were replaced with NA using the mutate() function to explicitly denote them as missing.
- The summary() function showed a high number of missing values, but further inspection revealed this was due to the data set containing results of 2 survey forms. Each survey form contained different sets of questions, as indicated within the "FORM_W42" variable. Each survey had been completed by roughly half the participants, resulting in misleading results in the number of missing values for all variables within the dataset. To enable a clearer view of the missing values, the data was split into two subsets based on the FORM_W42 variable using the subset() function.
- Missing value summaries were recalculated for each subset.

Handling Missing Values:

- The structure and summary of the subset containing the variables of interest was inspected.

- Missing values were identified and quantified.
- Listwise deletion was employed to handle missing values. Three new subsets were created, one for each scientist group (medical, environmental, nutrition) using the complete.cases() function to select only rows with no missing values for the variables of interest.
- The number and percentage of observations lost through listwise deletion were calculated.

Data Transformation:

- To aid interpretation, the 1-4 Likert scale variables were reverse coded using mutate() to create new variables where higher values indicated more positive perceptions.

Data Inspection:

- Univariate and bivariate statistics were computed for the variables of interest. A function called compute_stats() was defined to calculate summary statistics for each variable. It was applied to each using map_df() to produce tables of means, medians, standard deviations, ranges, skewness, and kurtosis. Sample sizes were also printed.
- The compute_mode() function was defined to find the statistical mode and applied to each variable.
- Multicollinearity was assessed using vif() to calculate the Variance Inflation Factor (VIF), and correlation matrices were produced for each scientist group using the cor() function and then visualized using corrplot() to check for multicollinearity.
- Scatterplot matrices were generated with pairs() to check linearity.
- Homoscedasticity and independence of residuals were verified using residual plots and autocorrelation function plots using plot() and acf().
- Normality of residuals was checked using QQ-plots and shapiro.test() to produce a Shapiro-Wilk test.

- Outliers were identified and inspected using Cook's distance plot.

Data Visualization:

- Plotted the effect sizes of predictors for confidence in medical scientists.
- Created separate plots for medical research scientists, environmental research scientists, and nutrition research scientists.
- Combined the plots for a comparative visualization across scientist groups.
- tidy() from the broom package was used to extract and tidy up the results from linear models.
- filter() from the dplyr package was used to filter out the intercept term from the tidied model results.
- ggplot() from the ggplot2 package was the main function to initiate the plotting.
- geom_col() from the ggplot2 package was used to create bar plots.
- coord_flip() from the ggplot2 package flipped the x and y axes for horizontal bar plots.
- labs() from the ggplot2 package added labels and titles to the plots.
- scale_x_discrete() and scale_y_continuous() from the ggplot2 package customized the scales for the x and y axes.
- scale_fill_viridis_d() from the ggplot2 package applied the Viridis color palette to the bars.
- theme() and related functions from the ggplot2 package customized the appearance of the plots.
- grid.arrange() and textGrob() from the gridExtra and grid packages respectively were used to combine multiple plots into a single plot and add common x, y labels, and a title.

Computational Reproducibility

For computational reproducibility document see Appendix or online repositories Google drive or Github repo .

Preliminary Analysis

Before interpreting the regression models, it's essential to address the underlying assumptions. The QQ-plots suggested that residuals were approximately normally distributed, even though the Shapiro-Wilk test indicated potential deviations. The relationships between predictors and dependent variables appeared linear, and the Variance Inflation Factor (VIF) values were within acceptable limits, suggesting multicollinearity wasn't a significant concern. While there were deviations from ideal assumptions, the robust nature of regression analysis provided confidence that these would not severely undermine the model's validity. All of the models here are weighted using the variable calculated by the Pew Research Centre to enable a generalisable result to the adult US population.

The first model to be tested was a weighted multiple linear regression was calculated to predict confidence in medical research scientists based on their competence, communication bias, responsibility, openness, and shared values. A significant regression model was identified ($F(5, 2166) = 138.4$, $p < .000$), accounting for approximately 24.22% of the variance in confidence ($R^2 = .2422$) with an adjusted R^2 of .2404. The predicted confidence in medical research scientists is represented by the equation: Confidence = 1.402 + 0.1908×Competence + 0.0818×Comm Bias - 0.0068×Responsibility + 0.1010×Openness + 0.2041×Shared Values. Among the predictors, competence ($t = 6.734$, $p < .000$), communication bias ($t = 2.837$, $p = .00459$), openness ($t = 4.603$, $p < .000$), and shared values (t = 8.352, p < .000) were significant predictors of confidence in medical research scientists. Notably, responsibility did not significantly predict confidence (t = -0.308, p = .75820)

Specifically:

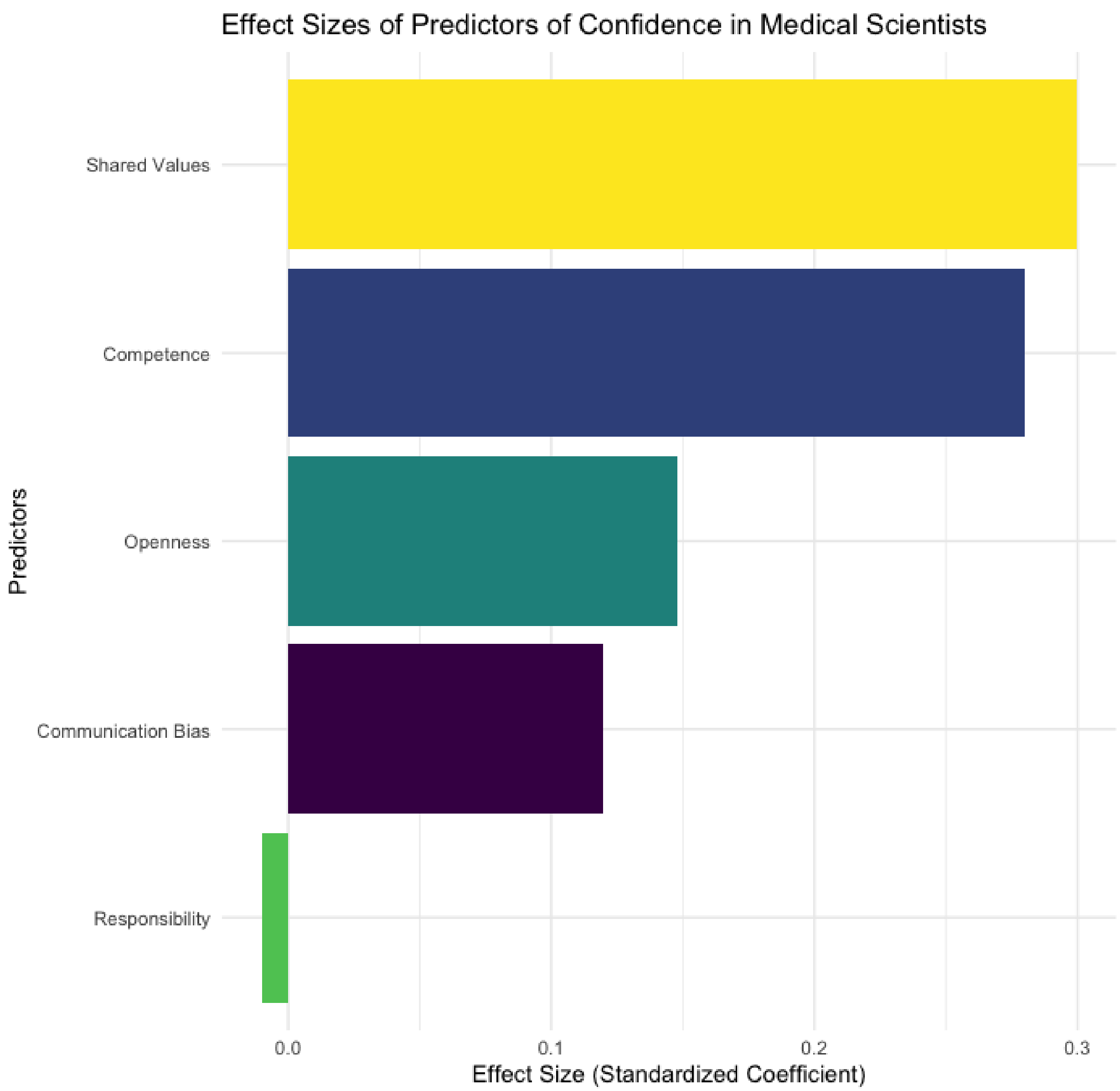
- Competence: For every unit increase in perceived competence, confidence in medical researchers increases by 0.1908 units, holding all other predictors constant (t = 6.734, p < .000).. This relationship is statistically significant.
- communication bias: For every unit increase in perceived communication bias, confidence in medical researchers increases by 0.0818 units, holding all other predictors constant (t = 2.837, p = .004). This relationship is statistically significant.
- Openness: For every unit increase in perceived openness, confidence in medical researchers increases by 0.1010 units, holding all other predictors constant. This relationship is statistically significant (p < 0.001).
- shared values: For every unit increase in perceived shared values, confidence in medical researchers increases by 0.2041 units, holding all other predictors constant. This relationship is statistically significant (p < 0.001).
- Responsibility: did not significantly predict confidence (t = -0.308, p = .75820), suggesting other factors might be at play or our sample might not have captured the full range of views on this predictor.

Interpretation based on Hypotheses:

- H1 is supported: Perceived competence positively predicts confidence in medical researchers.

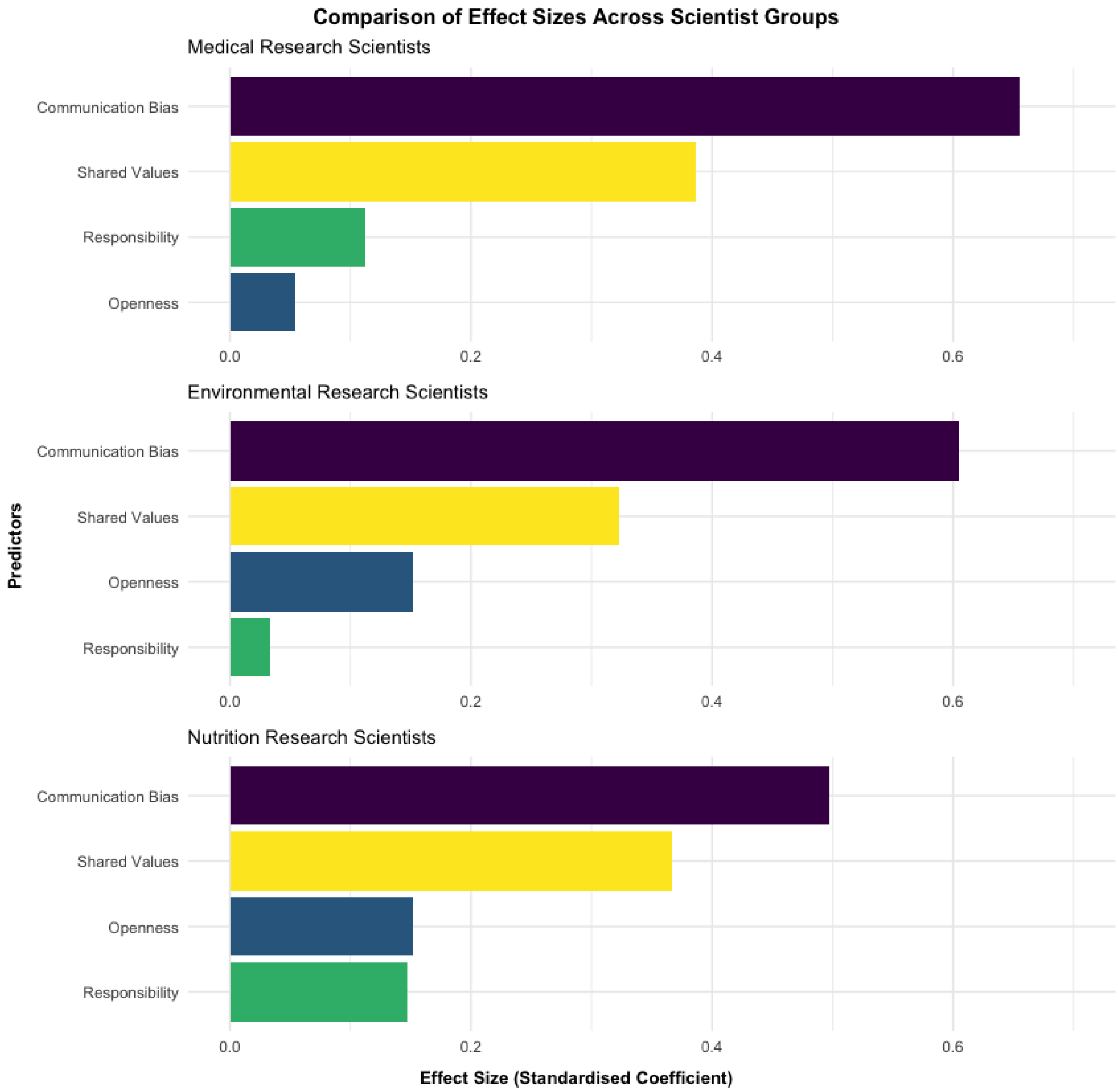
- H2 is partially supported: Among the factors representing perceived integrity, both perceived communication bias and perceived openness positively predict confidence in medical researchers. However, perceived responsibility does not.
- H3 is supported: Perceived benevolence, as represented by shared values positively predicts confidence in medical researchers.
- For H4, while both integrity (openness) and benevolence (shared values) are significant predictors, the coefficient for shared values (0.2041) is higher than that for competence (0.1908). This suggests that shared values might predict confidence to a slightly greater extent than competence. In summary, the regression model provides evidence supporting most of the hypotheses. Perceived competence, communication bias, openness, and shared values are all significant predictors of confidence in medical researchers. However, perceived responsibility does not significantly predict confidence in this context.

Figure 1. Effect Sizes of Predictors of Confidence in Medical Scientists Displayed As Standardised Coefficients.



Main Analysis: Tests of theory

Figure 2. Comparison of Effect Sizes Across Scientific Groups



Medical research scientists

The second model to be tested was a weighted multiple linear regression calculated to predict perceived competence of medical research scientists based on their communication bias, responsibility, openness, and shared values. A significant regression model was identified ($F(4, 2167) = 609.2$, $p < .000$), accounting for approximately 52.93% of the variance in perceived competence ($R^2 = .5293$) with an adjusted R^2 of .5285. The predicted competence of medical research scientists is represented by the equation: Competence =

0.9083 + 0.4223×Comm Bias + 0.0726×Responsibility + 0.0352×Openness + 0.2489×Shared Values.

Among the predictors:

- Communication Bias: For every unit increase in perceived communication bias, perceived competence in medical researchers increases by 0.4223 units, holding all other predictors constant. This relationship is statistically significant ($t = 21.244$, $p < .000$).
- Responsibility: For every unit increase in perceived responsibility, perceived competence in medical researchers increases by 0.0726 units, holding all other predictors constant. This relationship is statistically significant ($t = 4.377$, $p < .000$).
- Openness: For every unit increase in perceived openness, perceived competence in medical researchers increases by 0.0352 units, holding all other predictors constant. This relationship is statistically significant ($t = 2.119$, $p = 0.0342$).
- Shared Values: For every unit increase in perceived shared values, perceived competence in medical researchers increases by 0.2489 units, holding all other predictors constant. This relationship is statistically significant ($t = 14.035$, $p < .000$).

Interpretation based on Hypotheses:

- H5: Perceived integrity (openness, responsibility, communication bias) will positively predict competence perceptions for each scientific group. This hypothesis is supported as all three factors representing perceived integrity (communication bias, responsibility, and openness) are significant predictors of perceived competence.
- H6: Perceived integrity (openness, responsibility, communication bias) will positively predict competence perceptions to a greater extent than benevolence (shared values) for each scientific group. This hypothesis is partially supported. While all factors of perceived integrity are significant predictors, communication bias has the strongest relationship with

perceived competence, followed by shared values, responsibility, and then openness. In summary, the regression model provides evidence supporting the hypotheses. Perceived communication bias, responsibility, openness, and shared values are all significant predictors of perceived competence in medical researchers. Communication bias stands out as the strongest predictor among them.

Environmental scientists

The third model to be tested was a weighted multiple linear regression calculated to predict perceived competence of environmental scientists based on their communication bias, responsibility, openness, and shared values. A significant regression model was identified ($F(4, 2154) = 764.9$, $p < .000$), accounting for approximately 58.69% of the variance in perceived competence ($R^2 = .5869$) with an adjusted R^2 of .5861. The predicted competence of environmental scientists is represented by the equation: Competence = 0.8061 + 0.4322×Comm Bias + 0.0237×Responsibility + 0.1084×Openness + 0.2311×Shared Values.

Among the predictors:

- Communication Bias: For every unit increase in perceived communication bias, perceived competence in environmental researchers increases by 0.4322 units, holding all other predictors constant. This relationship is statistically significant ($t = 22.244$, $p < .000$).
- Responsibility: For every unit increase in perceived responsibility, perceived competence in environmental researchers increases by 0.0237 units, holding all other predictors constant. However, this relationship is not statistically significant ($t = 1.348$, $p = 0.178$).

- Openness: For every unit increase in perceived openness, perceived competence in environmental researchers increases by 0.1084 units, holding all other predictors constant. This relationship is statistically significant ($t = 6.108$, $p < .000$).
- Shared Values: For every unit increase in perceived shared values, perceived competence in environmental researchers increases by 0.2311 units, holding all other predictors constant. This relationship is statistically significant ($t = 12.085$, $p < .000$).

Interpretation based on Hypotheses:

- H5: Perceived integrity (openness, responsibility, communication bias) will positively predict competence perceptions for each scientific group. This hypothesis is partially supported in the context of environmental scientists. While communication bias and openness are significant predictors of perceived competence, responsibility is not.
- H6: Perceived integrity (openness, responsibility, communication bias) will positively predict competence perceptions to a greater extent than benevolence (shared values) for each scientific group. This hypothesis is supported for environmental scientists. Communication bias has the strongest relationship with perceived competence, followed by shared values, openness, and then responsibility. In summary, the regression model provides evidence supporting the hypotheses for environmental scientists. Perceived communication bias, openness, and shared values are all significant predictors of perceived competence in environmental researchers. However, perceived responsibility does not significantly predict competence in this context. Communication bias stands out as the strongest predictor among them.

Nutrition research scientists

The last model to be tested was a weighted multiple linear regression calculated to predict perceived competence of nutrition scientists based on their communication bias, responsibility, openness, and shared values. A significant regression model was identified ($F(4, 2137) = 668.3$, $p < .000$), accounting for approximately 55.57% of the variance in perceived competence ($R^2 = .5557$) with an adjusted R^2 of .5549. The predicted competence of nutrition scientists is represented by the equation: Competence = 0.7984 + 0.3400×Comm Bias + 0.1008×Responsibility + 0.1042×Openness + 0.2505×Shared Values.

Among the predictors:

- Communication Bias: For every unit increase in perceived communication bias, perceived competence in nutrition researchers increases by 0.3400 units, holding all other predictors constant. This relationship is statistically significant ($t = 17.274$, $p < .000$).
- Responsibility: For every unit increase in perceived responsibility, perceived competence in nutrition researchers increases by 0.1008 units, holding all other predictors constant. This relationship is statistically significant ($t = 6.152$, $p < .000$).
- Openness: For every unit increase in perceived openness, perceived competence in nutrition researchers increases by 0.1042 units, holding all other predictors constant. This relationship is statistically significant ($t = 6.314$, $p < .000$).
- Shared Values: For every unit increase in perceived shared values, perceived competence in nutrition researchers increases by 0.2505 units, holding all other predictors constant. This relationship is statistically significant ($t = 14.059$, $p < .000$).

Interpretation based on Hypotheses:

- H7: Perceived integrity (openness, responsibility, communication bias) will positively predict competence perceptions for each scientific group. This hypothesis is supported in the context of nutrition scientists. All three integrity predictors (communication bias, openness, and responsibility) are significant predictors of perceived competence.

- H8: Perceived integrity (openness, responsibility, communication bias) will positively predict competence perceptions to a greater extent than benevolence (shared values) for each scientific group. This hypothesis is partially supported for nutrition scientists.

Communication bias has the strongest relationship with perceived competence, followed by shared values, openness, and then responsibility. In summary, the regression model provides evidence supporting the hypotheses for nutrition scientists. All predictors, including perceived communication bias, openness, responsibility, and shared values, are significant predictors of perceived competence in nutrition researchers. Communication bias stands out as the strongest predictor among them.