

1      **Dossier: visualizing/ understanding decision choices in data analysis via**  
2      **decision similarity**  
3

4      **ANONYMOUS AUTHOR(S)**  
5

6      In data analysis, analysts are expected to clearly communicate the decisions they make, as these choices inform how results are  
7      interpreted and compared across studies. Such decisions – for example, selecting the degree of freedom for a smoothing spline – are  
8      often not systematically studied, since once an analysis is published, it is done seldom revisited or replicated with alternative choices.  
9      In this work, we focus on a body of data analysis studies on the effect of particulate matter on mortality, conducted by researchers  
10     worldwide, which naturally provide alternative analyses of the same question. We automatically extract analytic decisions from the  
11     published literature into structured data using Large Language Models (Claude and Gemini). We then proposed a pipeline to calculate  
12     paper similarity based on the semantic similarity of these extracted decisions and their reasons, and visualize the results through  
13     clustering algorithms. This approach offers an efficient way to study decision-making practices than traditional interviews. We also  
14     provide insights into the use of LLMs for text extraction tasks and the communication of analytic choices in data analysis practice.  
15

16     CCS Concepts: • **Applied computing** → *Document analysis*; • **Human-centered computing** → *HCI theory, concepts and models*.  
17

18     Additional Key Words and Phrases: Large language models  
19

20     **ACM Reference Format:**  
21

22     Anonymous Author(s). 2025. Dossier: visualizing/ understanding decision choices in data analysis via decision similarity. In *Proceedings*  
23     of CHI Conference on Human Factors in Computing Systems (CHI'26). ACM, New York, NY, USA, 19 pages. <https://doi.org/XXXXXXX>.  
24     XXXXXXX  
25

- 26     • Something about “analysis review” - Roger thinks it’s a better to have a new word for this.  
27     • demonstrate - analytically homogeneous - the table won’t look like that  
28

29     **1 Introduction**  
30

31     Decisions are everywhere in data analysis, from the initial data collection, data pre-processing to the modelling  
32     choices. These decisions will impact the final output of the data analysis, which may lead to different conclusions  
33     and policy recommendations. When such flexibility can be misused—through practices such as p-hacking, selective  
34     reporting, or unjustified analytical adjustments—it can inflate effect sizes or produce misleading results that meet  
35     conventional thresholds for statistical significance. They have been demonstrated through many-analysts experiments,  
36     where independent teams analyzing the same dataset to answer a pre-defined research question often arrive at markedly  
37     different conclusions. These practices not only compromise the validity of individual studies but also threaten the  
38     broader credibility of statistical analysis and scientific research as a whole.  
39

40     Multiple recommendations have been proposed to improve data analysis practices, such as pre-registration and  
41     multiverse analysis. Bayesian methods also offer a different paradigm to p-value driven inference for interpreting  
42     statistical evidence. Most empirical studies of data analysis practices focus on specially designed and simplified analysis  
43

---

44     Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not  
45     made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components  
46     of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to  
47     redistribute to lists, requires prior specific permission and/or a fee. Request permissions from [permissions@acm.org](mailto:permissions@acm.org).  
48

49     © 2025 ACM.  
50

51     Manuscript submitted to ACM  
52

53     Manuscript submitted to ACM

53 scenarios. While informative, these setups may not adequately capture the complexity of the data analysis with  
 54 significant policy implications. [In practice, studying the data analysis decisions with actual applications is challenging.]  
 55 Analysts may no longer be available for interviews due to job changes, and even when they are, recalling the full set  
 56 of decisions and thinking process made during the analysis is often infeasible. Moreover, only until the last decades,  
 57 analysis scripts and reproducible materials were not commonly required by journals for publishing. [As a result, it  
 58 remains challenging to study how analytical decisions are made.]  
 59

60 In this work, we focus on a specific class of air pollution modelling studies that estimate the effect size of particulate  
 61 matter (PM2.5 or PM10) on mortality, typically using Poisson regression or generalized additive models (GAMs).  
 62 While individual modelling choices vary, these studies often share a common structure: they adjust for meteorological  
 63 covariates such as temperature and humidity, apply temporal or spatial treatments, like including lagged variables and  
 64 may estimate the effect by city or region before combining results. Because these studies investigate similar scientific  
 65 questions using a shared modelling framework, they form a natural many-analyst setting. This allows us to examine, in  
 66 a real-world context, the range of analytical decisions made by different researchers addressing the same underlying  
 67 question.  
 68

69 In this work, we develop a structured tabular format to record the analytical decisions made by researchers in the air  
 70 pollution modelling literature. Using large language models (LLMs), we automate the extraction of these decisions from  
 71 published papers. This allows us to treat decisions as data – allowing us to track them over time, compare methodology  
 72 across papers, and query commonly used approaches. We further introduce a workflow to cluster studies based on  
 73 decision similarity, revealing three distinct groups of papers that reflect the modelling strategies differ in the European  
 74 and U.S. studies, which offers a new way to visualize the field in the air pollution mortality modelling.  
 75

76 The contribution of this work includes:

- 77 • A new approach to study data analysis decision choices through automatic extraction of decisions from scientific  
 78 literature using LLMs,
- 79 • A dataset compiled from 62 papers to study decision-making in air pollution mortality modelling,
- 80 • A pipeline to construct similarities between papers based on decision similarities, and
- 81 • Issues we found from existing data analysis reporting

82 The rest of the paper is organized as follows. In Section 2, we review the background on data analysis decisions.  
 83 Section 3 describes the data structure for recording decisions, the use of large language models to process research  
 84 papers, and the validation of LLM outputs. In Section 4, we present the method for calculating paper similarity based  
 85 on decision similarities. Section 5 reports the finding of our analysis, including the clustering of papers according to  
 86 similarity scores and sensitivity analyses related to LLM providers, prompt engineering, and LLM parameters. Finally,  
 87 Section 6 discusses the implications of our study.  
 88

## 90 2 Related work

### 91 2.1 Decision-making in data analysis

92 A data analysis is a process of making choices at each step, from the initial data collection to model specification, and  
 93 post-processing. Each decision represents a branching point where analysts choose a specific path to follow, and the  
 94 vast number of possible choices analysts can take forms what Gelman and Loken [18] describe as the “garden of forking  
 95 paths”. While researchers may hope their inferential results are robust to the specific path taken through the garden,  
 96 in practice, different choices can lead to substantially different conclusions. This has been empirically demonstrated  
 97

105 through “many analyst experiments”, where independent research groups analyze the same dataset to the same answer  
106 using their chosen analytic approach. A classic example is Silberzahn et al. [41], where researchers reported an odds  
107 ratio from 0.89 to 2.93 for the effect of soccer players’ skin tone on the number of red cards awarded by referees. Similar  
108 variability has been observed in structural equation modeling [39], applied microeconomics [22], neuroimaging [8],  
109 and ecology and evolutionary biology [19].

110 Examples above have rendered decision-making in data analysis as a subject to study in data science. To collect  
111 data on how analysts making decisions during data analysis, researchers have conducted interviews with analysts and  
112 researchers on data analysis practices [2, 24, 29], visualization of the decision process through the analytic decision  
113 graphics (ADG) [30]. Recently, Simson et al. [42] describes a participatory approach to decisions choices in fairness ML  
114 algorithms. Software tools have also developed to incorporate potential alternatives in the analysis workflow, including  
115 the DeclareDesign package [7] and the multiverse package [38]. The DeclareDesign package [7] introduces the  
116 MIDA framework for researchers to declare, diagnose, and redesign their analyses to produce a distribution of the  
117 statistic of interest, which has been applied in the randomized controlled trial study [6]. The multiverse package [38]  
118 provides a framework for researchers to systematically explore how different choices affect results and to report the  
119 range of plausible outcomes that arise from alternative analytic paths. Other systems have been developed to visualize  
120 multiverse analysis [31].

## 121 2.2 Visualization on scientific literature

122 Much of the work on IEEE visualizing scientific literature focuses on helping researchers stay aware of relevant  
123 publications, given the rapidly growing volume of scientific output and the difficulty of navigating it. Systems have  
124 been developed to support the discovery of relevant papers, where relevance is typically determined by keywords [23],  
125 citation information (e.g. citation list, co-citation) [13], or combinations with other relevant paper metadata (e.g. author,  
126 title) [5, 14, 17, 20]. More recent approaches incorporate text-based information from the abstract or sections of the  
127 paper to [obtain a better similar metric]. This includes using topic modelling [1], argumentation-based information  
128 retrieval [43], and text embedding [36]. While these metadata information and high level text-based information are  
129 valuable for discovering relevant papers, for data analysis, researchers need tools that help them *make sense* of the  
130 literature rather than simply *finding* it. Capturing the decisions and reasoning expressed during analyses within a  
131 similar theme can reveal common practices in the field and guide decisions choices in new applications. With recent  
132 advances in Large Language Models (LLMs), it has become possible to automatically extract structured information from  
133 unstructured text through prompting. This allows scientific literature to be clustered and visualized using information  
134 about the underlying decisions and reasoning made during analysis, providing a basis for studying analysts’ decision  
135 choices.

## 136 2.3 Air pollution mortality modelling

### 137 3 Extracting decisions from data analysis

#### 138 3.1 Decisions in data analysis

139 Decisions occur throughout the entire data analysis process – from the selection of variables and data source, to  
140 pre-processing steps to prepare the data for modelling, to the model specification and variable inclusion. In this work,  
141 we focus specifically on modelling decisions in the air pollution mortality modelling literature. These include the

choice of modelling approach, covariate inclusion and smoothing, and specifications of spatial and temporal structure. Consider the following excerpt from Ostro et al. [37]:

Based on previous findings reported in the literature (e.g., Samet et al. 2000), the basic model included a smoothing spline for time with 7 degrees of freedom (df) per year of data. This number of degrees of freedom controls well for seasonal patterns in mortality and reduces and often eliminates autocorrelation.

This sentence encode the following components of a decision:

- **variable:** time
- **method:** smoothing spline
- **parameter:** degree of freedom (df)
- **reason:** Based on previous findings reported in the literature (e.g., Samet et al. 2000); This number of degrees of freedom controls well for seasonal patterns in mortality and reduces and often eliminates autocorrelation.
- **decision:** 7 degrees of freedom (df) per year of data

The decision above is regarding a certain parameter in the statistical method, we categorize this as a “parameter” type decisions. Other types of decisions - such as spatial modelling structure or the inclusion of temporal lags - may not include an explicit method or parameter, but still reference a variable and rationale, which we will provide further examples below.

To record these decisions, we follow the tidy data principle [45], where each variable should be in a column, each observation in a row. In our context, each row represents a decision made by the authors of a paper and an analysis often include multiple decisions. To retain the original context of the decision, we extract the original text in the paper, without paraphrase or summarization, from the paper. Below we present an example of how to structure the decisions made in a paper, using the paper by Ostro et al. [37]:

Paper	ID	Model	variable	method	parameter	type	reason	decision
ostro	1	Poisson regression	temperature	smoothing spline	degree of freedom	parameter	NA	3 degree of freedom
ostro	2	Poisson regression	temperature	smoothing spline	degree of freedom	temporal	NA	1-day lag
ostro	3	Poisson regression	relative humidity	LOESS	smoothing parameter	parameter	to minimize Akaike's Information Criterion	NA
ostro	4	Poisson regression	model	NA	NA	spatial	to account for variation among cities	separate regression models fit in each city

209 Most decisions in the published papers are not explicitly stated, this could due to the coherence and conciseness of  
210 the writing or authors' decision to include only necessary details. Here, we identify a few common anomalies where  
211 decisions may be combined or omit certain fields:

- 212 1. **Authors may combine multiple decisions into a single sentence** for coherence and conciseness of the  
213 writing. Consider the following excerpt from Ostro et al. [37]:

214 Other covariates, such as day of the week and smoothing splines of 1-day lags of average temperature  
215 and humidity (each with 3 df), were also included in the model because they may be associated with  
216 daily mortality and are likely to vary over time in concert with air pollution levels.

217 This sentence contains four decisions: two for temperature (the temporal lag and the smoothing spline parameter)  
218 and two for humidity. These decisions should be structured as separate entries.

- 219 2. **The justification does not directly address the decision choice.** In the example above, the stated rationale  
220 ("and are likely to vary over time in concert with air pollution levels") supports the general inclusion of temporal  
221 lags but does not justify the specific choice of 1-day lag over alternatives, such as 2-day average of lags 0 and 1  
222 (lag01) and single-day lag of 2 days (lag2). As such, the reason field should be recorded as NA.

- 223 3. **Some decisions may be omitted because they are data-driven.** For instance, Katsouyanni et al. [26] states:  
224 The inclusion of lagged weather variables and the choice of smoothing parameters for all of the weather  
225 variables were done by minimizing Akaike's information criterion.

226 In this case, while the method of selection (minimizing AIC) is specified, the actual degree of freedom used is not.  
227 Such data-driven decisions may be recorded with "NA" in the decision field, but the reason field should still be recorded  
228 as "by minimizing Akaike's information criterion"

- 229 4. **Information required to interpret the decision may be distributed across multiple sections.** In the  
230 previous example, "weather variables" refers to mean temperature and relative humidity, as defined earlier in  
231 the text. This requires cross-referencing across sections to identify the correct variables associated with each  
232 modeling choice.

### 233 3.2 Automatic reading of literature with LLMs

234 **TODO:** Prompt engineering: these models may paraphrase or hallucinate unless explicitly told not to since it is  
235 generative in nature based on the predicted probability of the next word from the text and the instruction

236 **TODO:** The Prompt Report: A Systematic Survey of Prompt Engineering Techniques <https://arxiv.org/pdf/2406.06608.pdf>  
237 While decisions can be extracted manually from the literature, this process is labor-intensive and time-consuming.  
238 Recent advances in Large Language Models (LLMs) have demonstrated potential for automating the extraction of  
239 structured information from unstructured text [ref]. In this work, we use LLMs to automatically identify decisions  
240 made by authors during their data analysis processes.

241 Text recognition from PDF document relies on Optical Character Recognition (OCR) to convert scanned images into  
242 machine-readable text – capability currently offered by Anthropic Claude and Google Gemini. We instruct the LLM  
243 to generate a markdown file containing a JSON block that records extracted decisions, which can then be read into  
244 statistical software for further analysis. The exact prompt feed to the LLM is provided in the Appendix. The `ellmer`  
245 package [46] in R is used to connect to the Gemini and Claude API, providing the PDF attachment and the prompt in a  
246 markdown file as inputs.

### 261 3.3 Review the LLM output

- 262 • TODO something about result validation of LLM output

263  
264 The shiny app is designed to provide users a visual interface to review and edit the decisions extracted by the LLM  
265 from the literature. The app allows three actions from the users: 1) *overwrite* – modify the content of a particular  
266 cell, equivalently `dplyr::mutate(xxx = ifelse(CONDITION, "yyy" , xxx))`, 2) *delete* – remove a particular cell,  
267 `dplyr::filter(!(CONDITION))`, and 3) *add* – manually enter a decision, `dplyr::bind_rows()`. Figure 1 illustrates  
268 the *overwrite* action in the Shiny application, where users interactively filter the data and preview the rows affected by  
269 their edits—in this case, changing the model entry from “generalized additive Poisson time series regression” to the  
270 less verbose “Poisson regression”. Upon confirmation, the corresponding tidyverse code is generated, and users can  
271 download the edited table and incorporate the code into their R script.  
272

paper	id	model	variable	method	parameter	type	reason	decision
anderson2008size	1	generalized additive Poisson time series regression	temperature	smoothing spline	degrees of freedom	parameter	NA	4 or 5
anderson2008size	2	generalized additive Poisson time series regression	deew-point temperature	smoothing spline	degrees of freedom	parameter	NA	4 or 5
anderson2008size	3	generalized additive Poisson time series regression	calendar time	smoothing spline	degrees of freedom per year	parameter	NA	3, 4 or 5
anderson2008size	4	generalized additive Poisson time series regression	polynomial concentrations	NA	N/A	temporal	NA	log(0-5) days examined
barrett2004ar	1	case-crossover model	model	NA	N/A	temporal	NA	use fixed 28-day window w/ 1 day around case day to control for long-term trend, seasonal, and other time-varying effects by design
barrett2004ar	2	case-crossover	temperature	NA	N/A	temporal	NA	use current relative temperature to control for weather
barrett2004ar	3	case-crossover	temperature extremes	percentile	Id and 99th percentile	parameter	NA	to control for extremes of hot and cold days
barrett2004ar	4	random effects meta-analysis	model	NA	N/A	spatial	NA	to estimate average effect of cities across cities using random effects meta-analysis
barrett2004ar	5	case-crossover model	air pollutants	NA	N/A	temporal	NA	use average of current and previous day to control for weather
bel2003seasonal	1	2-stage Bayesian hierarchical model	temperature	natural cubic spline	6 degrees of freedom	parameter	NA	6 degrees of freedom
bel2003seasonal	2	2-stage Bayesian hierarchical model	deew-point temperature	natural cubic spline	6 degrees of freedom	parameter	NA	6 degrees of freedom

**1**

paper	id	model	variable	method	parameter	type	reason	decision
anderson2008size	1	Poisson regression	temperature	smoothing spline	degrees of freedom	parameter	NA	4 or 5
anderson2008size	2	Poisson	deew-point temperature	smoothing spline	degrees of freedom	parameter	NA	4 or 5
anderson2008size	3	Poisson regression	calendar time	smoothing spline	degrees of freedom per year	parameter	NA	3, 4 or 5
anderson2008size	4	Poisson regression	polynomial concentrations	NA	N/A	temporal	NA	log(0-5) days examined

**2**

paper	id	model	variable	method	parameter	type	reason	decision
barrett2004ar	1	case-crossover model	model	NA	N/A	temporal	NA	to control for long-term trend, seasonal, and other time-varying effects by design
barrett2004ar	2	case-crossover	temperature	NA	N/A	temporal	NA	use current relative temperature to control for weather effects
barrett2004ar	3	case-crossover	temperature extremes	percentile	Id and 99th percentile	parameter	NA	to control for extremes of hot and cold
barrett2004ar	4	random effects meta-analysis	model	NA	N/A	spatial	NA	use average of current and previous day to control for weather

**3**

paper	id	model	variable	method	parameter	type	reason	decision
anderson2008size	1	Poisson regression	temperature	smoothing spline	degrees of freedom	parameter	NA	4 or 5
anderson2008size	2	Poisson regression	deew-point temperature	smoothing spline	degrees of freedom	parameter	NA	4 or 5
anderson2008size	3	Poisson regression	calendar time	smoothing spline	degrees of freedom per year	parameter	NA	3, 4 or 5
anderson2008size	4	Poisson regression	polynomial concentrations	NA	N/A	temporal	NA	log(0-5) days examined

**4**

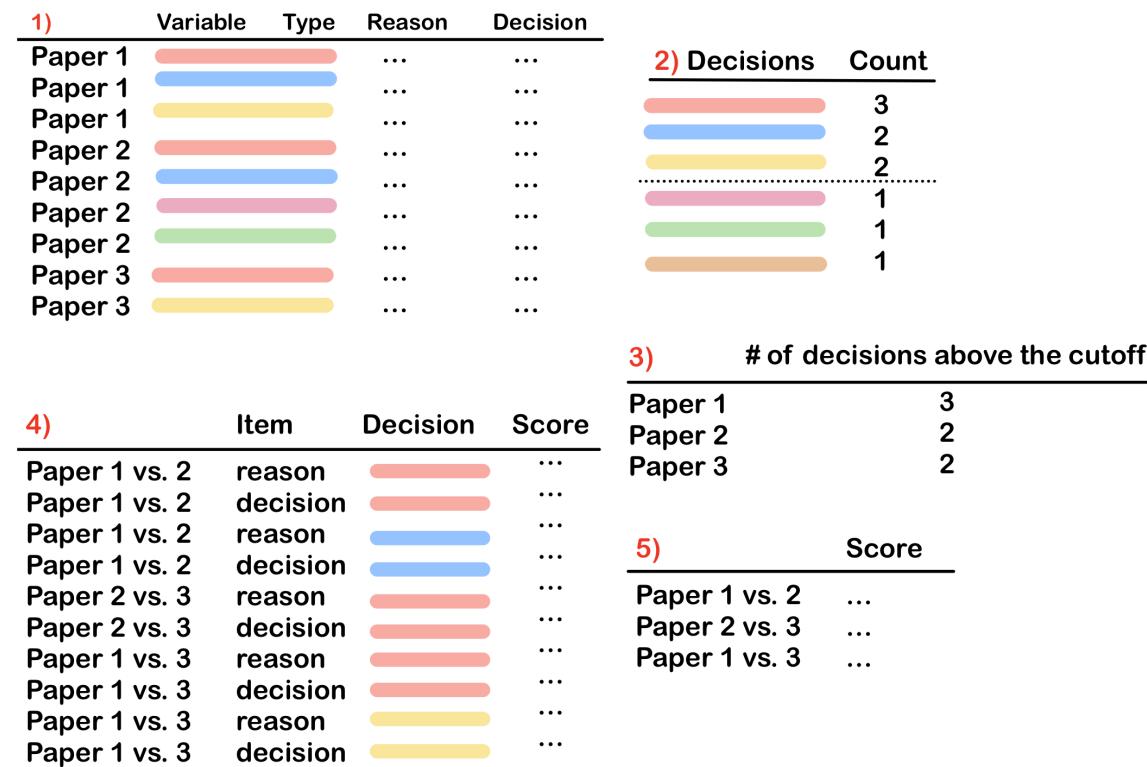
paper	id	model	variable	method	parameter	type	reason	decision
barrett2004ar	1	case-crossover model	air pollutants	NA	N/A	temporal	NA	use average of current and previous day to control for weather
barrett2004ar	2	2-stage Bayesian hierarchical model	temperature	natural cubic spline	6 degrees of freedom	parameter	NA	6 degrees of freedom
barrett2004ar	3	2-stage Bayesian hierarchical model	deew-point temperature	natural cubic spline	6 degrees of freedom	parameter	NA	6 degrees of freedom
barrett2004ar	4	2-stage Bayesian hierarchical model	time	natural cubic spline	6 degrees of freedom per year	parameter	NA	6 degrees of freedom per year

300 Fig. 1. The Shiny application interface for editing Large Language Model (LLM)-generated decisions (overwrite, delete, and add). (1)  
301 the default interface after loading the input CSV file. (2) The table view will update interactively upon the user-defined filter condition  
302 – expressed using `dplyr::filter()` syntax (e.g., `paper == anderson2008size`”), (3) The user edits the model column to “Poisson  
303 regression” and applies the change by clicking the Apply changes button. The table view updates to reflect the changes (4) After  
304 clicking the Confirm button, the corresponding tidyverse code is generated, and the table view returns to its original unfiltered view.  
305 The edited data can be downloaded by clicking the Download CSV button.

## 306 4 Calculating paper similarity

307 Once the decisions have been extracted and validated, this opens up a structured data for analyzing these information.  
308 For example, we can compare whether author’s choices at different times changes, or across decisions varies at different  
309 regions. In this section, we present a method to calculate paper similarity based on the decisions shared in the paper  
310  
311 Manuscript submitted to ACM

313 pairs. The goal is to construct a distance metric based on similarity of the decision choice among papers that could  
 314 be further used for clustering paper based on choices made by different authors in the literature. An overview of the  
 315 method is illustrated in Figure 2.  
 316



345 Fig. 2. Workflow for calculating paper similarity based on decision choices: (1) standardize variable names, (2) identify most frequent  
 346 variable-type decisions across all papers, (3) identify papers with at least x identified decisions, (4) calculate decisions similarity  
 347 score on the *decision* and *reason* fields using transformer language models, e.g. BERT, (5) calculate paper similarity score based on  
 348 aggregating decision similarity scores.

- 349
- 350 • TODO some discussion on what it means by for two papers to be similar based on decisions.

351 The calculation of paper similarity is based on the similarity of decisions shared by each paper pair. A decision  
 352 comparable in two papers are the ones that share the same variable and type, e.g. temperature and parameter (a decisions  
 353 on the choosing the statistical method *parameter* for the *temperature* variable), or humidity and temporal (any *temporal*  
 354 treatment, e.g. choice of lag value for the *humidity* variable). While many decisions share a similar variable, different  
 355 authors may refer to them with slightly different names, such as “mean temperature” and “average temperature”, hence  
 356 variable names are first standardized to a common set of variable names. For example, “mean temperature” and “average  
 357 temperature” are both standardized to “temperature”. Notice that “dewpoint temperature” is standardized into “humidity”  
 358 since it is a proxy of temperature to achieve a relative humidity (RH) of 100%. For literature with a common theme,  
 359 there is usually a set of variables that shared by most papers and additional variables are justified in individual research.  
 360 For our air pollution mortality modelling literature, we standardize the following variable names:  
 361

Table 2. THis is hte caption

Missing reason	Missing decision	
	FALSE	TRUE
FALSE	95 (32.4%)	13 (4.4%)
TRUE	179 (61.1%)	6 (2%)

- **temperature**: “mean temperature”, “average temperature”, “temperature”, “air temperature”, “ambient temperature”
- **humidity**: “dewpoint temperature” and its hyphenated variants, relative humidity”, “humidity”
- **PM**: “pollutant”, “pollution”, “particulate matter”, “particulate”, “PM10”, “PM2.5”
- **time**: “date”, “time”, “trends”, “trend”

Depending on the specific pairs, papers have varied number of decisions that can be compared and aggregated. While paper similarities can be computed for all paper pairs, using the similarity of one or two pair of decisions to represent paper similarity is less ideal. Hence, before calculating the text similarity of decisions, we also include two optional steps to identify and subset the most frequent decisions across papers, and to retain only papers that report more than a certain number of frequent decisions. Research questions in different fields may have different levels of homogeneity, depending on the maturity of the field and for air pollution mortality modelling, it is helpful to focus on decisions and papers that share a substantial number of decisions.

To assign numerical value for the similarity of reason, we use a transformer language model, such as BERT, to measure the semantic text similarity between the decision itself and its justification. The decision similarity is calculated by comparing the *decision* and *reason* fields of the decisions in each paper pair. To obtain paper similarity, we average the decision similarities across all decisions in each paper pair and other method can be customized for aggregation. The resulting paper similarity score can be used as a distance matrix to cluster papers based on their decision choices to understand the common practices in the investigated literature.

## 5 Results

### 5.1 Air pollution mortality modelling

- a characterization of the field, what are the common variables included, what smoothing methods are used, what are the options for temporal lags often considered, how are models generally estimated spatially.
- For lee2006association, it is not clear what specific smoothing method the sentence “smooth function of the day of study” refers to.

The results follows examines 57 papers for modelling the effect of particulate matters on mortality based on Gemini for parsing the decision choices. The results from Anthropic Claude is reported in the sensitivity analysis section in Section 5.2. From the 57 papers, we extracted 273 decisions (~ 5 decisions each paper). Out of which the most are parameter-related decisions and temporal decision, accounting for 1% and 43%, respectively. Table 2 summarizes the missingness of the decisions and reason for each record. While most papers provide the choice of their decision (e.g. use of 5 degree of freedom), a 61% of the decisions are missing the reason for the choice. This reveals a prevalent phenomenon that authors tend to not justify the choice being made, which requires attention. We also observe data

417 quality with the extraction: for example in Lee et al. [28], the variable recorded is “smoothing parameter”. Authors are  
 418 unclear about the delivery Specify how much of validation and review has been done.  
 419

420 Table 3. Count of xxx in the Gemini dataset  
 421

422	Variable	Type	Count
423	time	parameter	47
424	PM	temporal	38
425	temperature	parameter	37
426	humidity	parameter	25
427	temperature	temporal	23
428	humidity	temporal	18
429	PM	parameter	7
430	time	temporal	5

431 Table 3 shows the most common decision for air pollution modelling is to the parameter choice for time, PM,  
 432 temperature, and humidity. Given the count of decisions included by all the papers, we decide to include the first 6  
 433 most common variable-type decisions in the analysis to calculate the decision similarities.  
 434

435 Table 4 shows number of knots for the natural spline and degree of freedom for smoothing spline for time, humidity  
 436 and temperature variables. [TODO]  
 437

- 438 • The choice of knot for natural spline is less varied than the choice of degree of freedom for smoothing spline
- 439 • The choice for temperature and humidity tends to be the same, potentially due to they are both weather related  
 440 variables.
- 441 • The choice for time is more varied. and we observe interesting choices of 7.7 in Castillejos et al. [12] and flexible  
 442 choice of 30 and 100 in Moolgavkar [34] and Moolgavkar [35], respectively.
- 443 • most paper choices a fix number for the smoothing parameter while Schwartz [40] choose a proportion of the  
 444 data: “50% of the data”, “5% of the data”

445 Table 5 shows ....

446 [look at for one type of decision (time) - what are the choices made by different papers]

447 Table 4. Most common decisions for humidity and temperature variables in the Gemini dataset  
 448

449 Method	450 Variable	451 Decision
452 natural spline	humidity	3, 4
453 natural spline	temperature	3, 4, 6
454 natural spline	time	1, 3, 4, 6, 7, 8, 12
455 smoothing spline	humidity	2, 3, 4, 6, 8, 50% of the data
456 smoothing spline	temperature	2, 3, 4, 6, 8, 50% of the data
457 smoothing spline	time	1, 3, 4, 5, 6, 7, 7.7, 8, 9, 10, 12, 30, 100, NA, 5% of the data

Table 5. Temporal lag decisions for PM, temperature, and humidity variables in the Gemini dataset

Lag type	Variable	Decision
multi-day average	PM	0-1, 0-2, 0-3, 0-4, 0-5, 0-7, 1-0, 1-5
multi-day average	humidity	0-1, 0-2, 0-3, 0-5, 1-3, 1-5
multi-day average	temperature	0-1, 0-2, 0-3, 0-5, 0-7, 1-3
single-day lag	PM	lag 0, lag 1, lag 2, lag 3, lag 4, lag 5
single-day lag	humidity	lag 0, lag 1, lag 2, lag 3, lag 4, lag 5, lag 6, lag 7
single-day lag	temperature	lag 0, lag 1, lag 2, lag 3, lag 4, lag 5

Figure 3 shows the clustering of the 57 papers based on the decision similarity scores. The dendrogram is generated using hierarchical clustering, and the labels are colored according to the most common smoothing method used in each paper. The clustering reveals three distinct groups of papers, which reflect the modelling strategies differ in the European and U.S. studies [more on the APHENA]. The first group (left) primarily uses LOESS smoothing, while the second group (middle) employs natural splines, and the third group (right) uses smoothing splines.

- choose the ones in the baseline model
- don't include other options considered, only the final value used in the model
- no sensitivity analysis
- only consider PM2.5 and PM10 not other pollutants

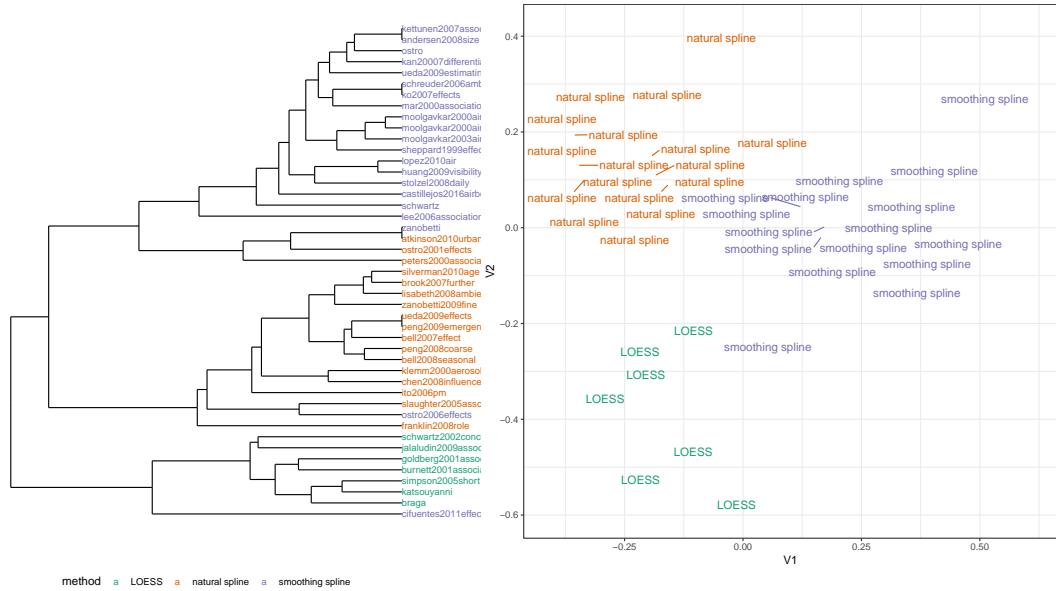


Fig. 3. The dendrogram (left) and multi-dimensional scaling (MDS) (right) based on paper similarity distance for 62 air pollution mortality modelling literature. The papers are colored by the most common smoothing method used. The MDS reveals the three distinct groups of papers. This grouping corresponds to the modelling strategies differ in the European and U.S. studies, documented in ALPHENA.

521    **5.2 Sensitivity analysis**

522  
 523 In this section, we examine the reproducibility for using LLMs for text extraction tasks in Section 5.2.1, discrepancies  
 524 between different LLM models: Gemini (gemini-2.0-flash) and Claude (claude-3-7-sonnet-latest) in Section 5.2.2,  
 525 and the sensitivity of our paper similarity calculation pipeline to the choice of text model used for computing decision  
 526 similarity scores in Section 5.2.3.  
 527

528    *5.2.1 LLM reproducibility.* For our text extraction task, we test the reproducibility of Gemini (gemini-2.0-flash) by  
 529 repeating the text extraction task 5 times for each of the 62 papers. For each of the 31 papers, five runs yield  $5 \times 4 / 2 = 10$   
 530 pairwise comparisons per field and including both the “reason” and “decision” fields results in a total of  $31 \times 10 \times 2 = 620$   
 531 pairs. We exclude the pairs that have different number of decisions since it would require manually align the decision to  
 532 compare and this left us with 449 out of 620 (72%) pairwise comparisons. Table 6 shows an example of such comparison  
 533 in Andersen et al. [3], where all the four reasons are identical among the two runs, hence a zero number of difference.  
 534

535    Table 6. An example of comparing the text extraction in decisions in Andersen 2008.  
 536

539    Variable	Run1	Run2
540    NCTot	6day average (lag 05)	6day average (lag 05)
541    calendar time	3 4 or 5 dfyear	3 4 or 5 dfyear
542    dew-point temperature	4 or 5 df	4 or 5 df
543    temperature	4 or 5 df	4 or 5 df

544    Table 7 summarizes the number of differences observed in each pairwise comparison. Among all comparisons, 80%  
 545 produce the identical text in reason and decision. The discrepancies come from the following reasons:  
 546

- 547    • Gemini extracted different length for the same decision, e.g. in Kan et al. [25], some runs may extract “singleday  
 548    lag models underestimate the cumulative effect of pollutants on mortality 2day moving average **of current**  
 549    **and previous day concentrations** (lag=01), while others extract “singleday lag models underestimate the  
 550    cumulative effect of pollutants on mortality 2day moving average (lag=01)”. Similarly, for decisions, some runs  
 551    may yield “10 df for total mortality”, while other runs yield “10 df”. Similar extraction appears in Breitner et al.  
 552    [9].
- 553    • Gemini fails to extract reasons in some runs but not others, e.g. in Burnett et al. [10], the first run generates  
 554    NAs in the reasons, but the remaining four runs are identical. In Ueda et al. [44] and Castillejos et al. [12], runs  
 555    1 and 5 fail to extract the reasons and produce the same incomplete version, whereas runs 2, 3, and 4 produce  
 556    accurate versions with reasons populated.

557    Table 7. Number of differences in the reason and decision fields across Gemini runs for papers with consistent number of decisions  
 558    across runs.  
 559

566    Num. of difference	Count	Proportion (%)
567    0	358	79.73
568    1	12	2.67
569    2	8	1.78

573 Table 7. Number of differences in the reason and decision fields across Gemini runs for papers with consistent number of decisions  
 574 across runs.

576	Num. of difference	Count	Proportion (%)
577	3	0	0.00
578	4	24	5.35
579	5	12	2.67
580	6	3	0.67
581	7	0	0.00
582	8	10	2.23
583	9	6	1.34
584	10	10	2.23
585	11	6	1.34
586	Total	449	100.00

591  
 592  
 593  
 594  
 595  
 596  
 597 5.2.2 *LLM models*. Reading text from PDF document requires Optical Character Recognition (OCR) to convert images  
 598 into machine-readable text, which currently is only supported by Anthropic Claude (claude-3-7-sonnet-latest) and  
 599 Google Gemini (gemini-2.0-flash).

600  
 601 We compare the number of decisions extracted by Claude and Gemini across all 62 papers in Figure 4. Each point  
 602 represents a paper, with the x- and y-axes showing the number of decisions extracted by Claude and Gemini, respectively.  
 603 The dashed 1:1 line marks where both models extract the same number of decisions. Most points fall below this line,  
 604 indicating that Claude extracts more decisions – often from data pre-processing or secondary data analysis steps  
 605 requiring more manual validation – whereas Gemini focuses more on modelling choices relevant to our analysis. Some  
 606 of these decisions captured by Claude are  
 607

- 608 • the definition of “cold day” and “hot day” indicators in Dockery et al. [16] (“defined at the 5th/ 95th percentile”),
- 609 • the choice to summarize NO<sub>2</sub>, O<sub>3</sub>, and SO<sub>2</sub> using a “24 hr average on variable” in Huang et al. [21], and
- 610 • the definition of black smoke and in Katsouyanni et al. [26] for secondary analysis (“restrict to days with BS  
 611 concentrations below 150 µg/m<sup>2</sup>”).

612 Gemini sometimes also include irrelevant decisions, such as in Mar et al. [33], where secondary analysis choices like  
 613 “0-4 lag days” for air pollution exposure variables (CO, EC, K<sub>S</sub>, NO<sub>2</sub>, O<sub>3</sub>, OC, Pb, S, SO<sub>2</sub>, TC, Zn) are captured. However,  
 614 these cases are less frequent, resulting in outputs with less noise overall.

615 For both Claude and Gemini, we find they fail to link the general term “weather variables” to the specific weather  
 616 variables. For example Gemini misses this link in Dockery et al. [16] and Burnett et al. [11], while Claude does so in  
 617 Dockery et al. [16] and Katsouyanni et al. [26]. Although our prompt specified that some decisions may require linking  
 618 information across sentences and paragraphs to identify the correct variable, this instruction doesn’t appear to be  
 619 applied consistently.

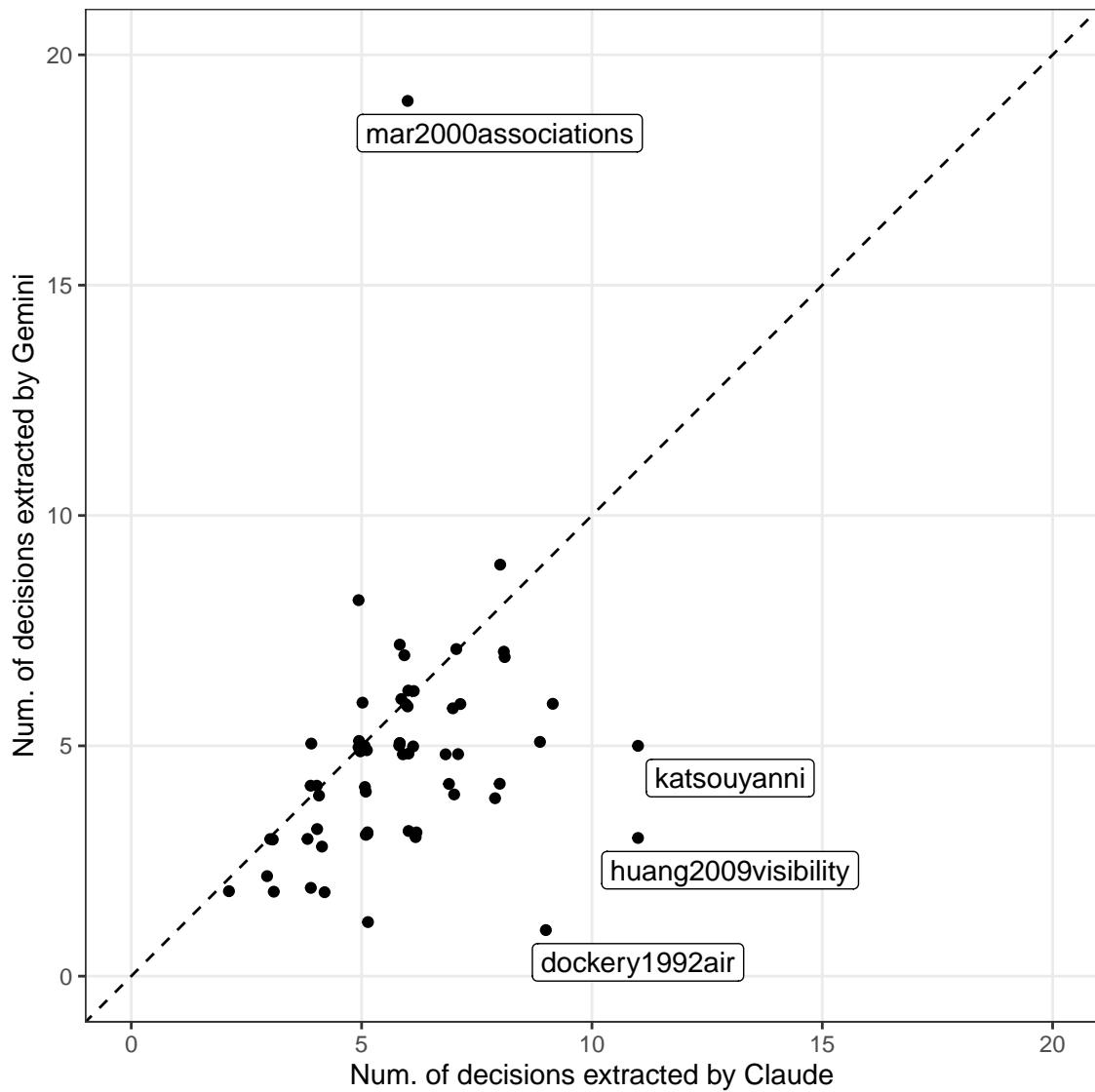


Fig. 4. Comparison of decisions extracted by Claude and Gemini. Each point represents a paper, with the x- and y-axes showing the number of decisions extracted by Claude and Gemini, respectively. The dashed 1:1 line marks where both models extract the same number of decisions. Most points fall below this line, suggesting Claude extracts more decisions – often including noise from data pre-processing or secondary data analysis steps – which requires additional manual validation.

5.2.3 *Text model.* We have conducted sensitivity analysis on the text model for obtaining the decision similarity score from the Gemini outputs. The tested language models tested include

- 1) BERT by Google [15],
- 2) RoBERTa by Facebook AI [32], trained on a larger dataset (160GB v.s. BERT's 15GB),
- 3) XLNet by Google Brain [47], and

677 two domain-trained BERT models:

- 678 4) sciBERT [4], trained on scientific literature, and  
 679 5) bioBERT [27], trained on PubMed and PMC data.

680 Figure 5 presents the distribution of the decision similarity (left) and paper similarity (right) for each text model.  
 681 At decision level, the BERT model produces the widest variation across all five models, while the similarity scores  
 682 from XLNet are all close to 1. These scores are not comparable across models since the difference of the underlying  
 683 transformer architecture. However, the paper similarity scores from each model are comparable and Figure 6 shows the  
 684 multi-dimensional scaling (MDS) of the paper similarity scores from each text model: all showing a similar clustering  
 685 pattern of the three main smoothing methods.  
 686

688

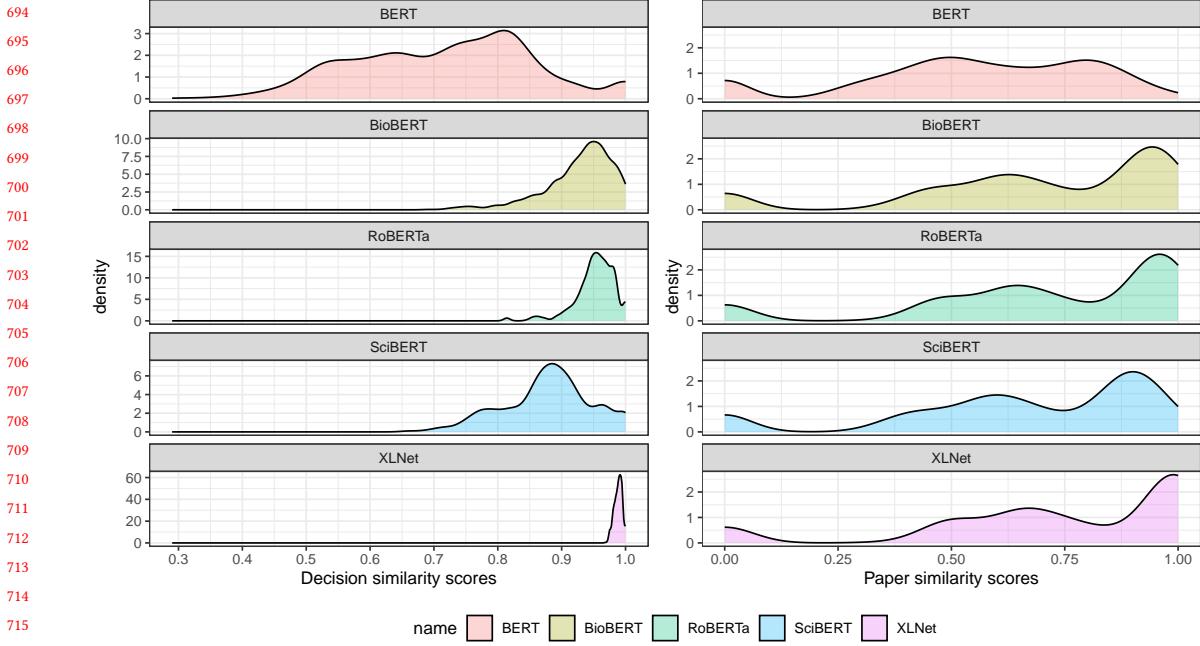
689

690

691

692

693



714

715

716

717

718 Fig. 5. Distribution of decision similarity (left) and paper similarity (right) scores for five different text models (BERT, BioBERT,

719 RoBERTa, SciBERT, and XLNet). The default language model, BERT, produces the widest variation across the five models, while

720 the similarity scores form XLNet are all close to 1. The model BioBERT, RoBERTa, and SciBERT yield decision similar scores mostly

721

722

723

724

725

726

727

728

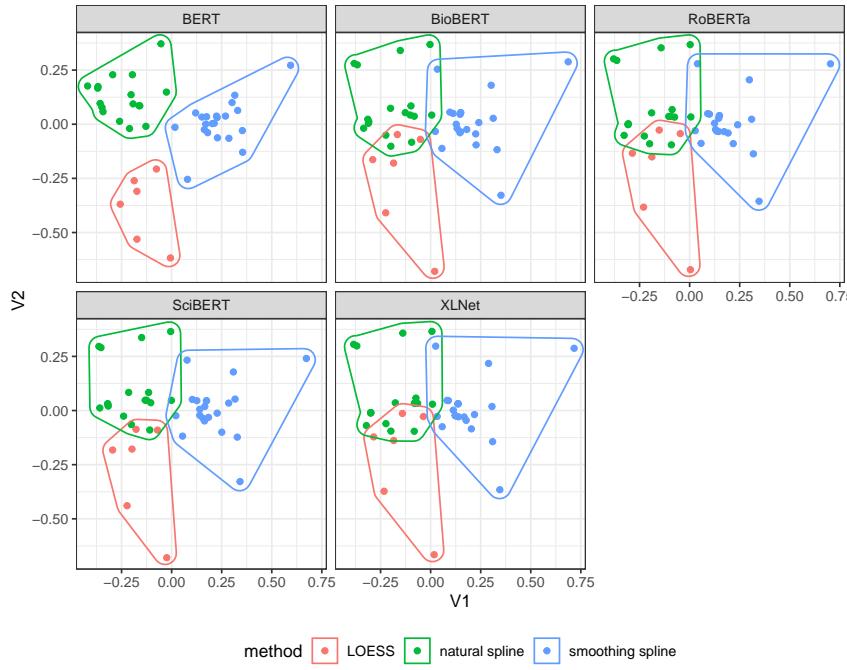


Fig. 6. The multi-dimensional scaling (MDS) of the paper similarity scores from each text model: all showing a similar clustering pattern of the three main smoothing methods. The points are colored by the most common method used in the paper, and the hulls are drawn around each method group.

## 6 Discussion

- Address how sensitivity analysis is/ is not relevant
- Only prompting engineering is used to extract decisions from the literature. We expect that fine-tuning the model on statistical or domain-specific literature to yield more robust performance on the same document, though it would require substantially more training effort.
- people from the NYU-LMU workshop are interested to have code script attached as well because people can do one thing in the script but report another in the paper - it would be interesting to compare the paper and the script with some syntax extraction.
- Spatial decisions are generally not well captured because it often conducted uniformly as estimating the city individually to accommodate city heterogeneity. Some papers only consider a handful of cities, while in larger studies the individual city effects are then pooled together using random effect.
- Validation of the output:

the nature of the task: Our task involve a reasoning component in that it requires causal reasoning to identify the decisions made by the authors, and its justification/ rationale, rather than purely summarizing the text through pattern-matching.

- some decisions are more varied than others and can be reported by different ways. e.g. the most common way to report the smoothing parameter for time is the number of knots/ degree of freedom per year. While authors

781 may report this number in different ways, i.e. “every 30 days”. A secondary processing with LLM may be useful  
 782 to align the raw text into the same reporting unit.s  
 783

## 784 References

- 785 [1] Eric Alexander, Joe Kohlmann, Robin Valenza, Michael Witmore, and Michael Gleicher. 2014 ieee conference on visual analytics science and  
 786 technology (vast). pages 173–182, 10 2014. doi: 10.1109/VAST.2014.7042493. URL <https://ieeexplore.ieee.org/document/7042493>.
- 787 [2] Sara Alspaugh, Nava Zokaei, Andrea Liu, Cindy Jin, and Marti A. Hearst. Futzting and moseying: Interviews with professional data analysts on  
 788 exploration practices. *IEEE Transactions on Visualization and Computer Graphics*, 25(1):22–31, 01 2019. doi: 10.1109/TVCG.2018.2865040. URL  
 789 <https://ieeexplore.ieee.org/document/8440815>.
- 790 [3] Z. J. Andersen, P. Wahlin, O. Raaschou-Nielsen, M. Ketzel, T. Scheike, and S. Loft. Size distribution and total number concentration of ultrafine  
 791 and accumulation mode particles and hospital admissions in children and the elderly in copenhagen, denmark. *Occupational and Environmental  
 792 Medicine*, 65(7):458–466, 07 2008. doi: 10.1136/oem.2007.033290. URL <https://oem.bmjjournals.org/content/65/7/458>. Publisher: BMJ Publishing Group Ltd  
 793 Section: Original article PMID: 17989204.
- 794 [4] Iz Beltagy, Kyle Lo, and Arman Cohan. Proceedings of the 2019 conference on empirical methods in natural language processing and the  
 795 9th international joint conference on natural language processing (emnlp-ijcnlp). pages 3613–3618, Hong Kong, China, 2019. Association for  
 796 Computational Linguistics. doi: 10.18653/v1/D19-1371. URL <https://www.aclweb.org/anthology/D19-1371>.
- 797 [5] Steven Bethard and Dan Jurafsky. Cikm '10: International conference on information and knowledge management. pages 609–618, Toronto ON  
 798 Canada, 10 2010. ACM. doi: 10.1145/1871437.1871517. URL <https://dl.acm.org/doi/10.1145/1871437.1871517>.
- 799 [6] Dorothy V. M. Bishop and Charles Hulme. When alternative analyses of the same data come to different conclusions: A tutorial using declaredesign  
 800 with a worked real-world example. *Advances in Methods and Practices in Psychological Science*, 7(3):25152459241267904, 07 2024. doi: 10.1177/  
 801 25152459241267904. URL <https://doi.org/10.1177/25152459241267904>. Publisher: SAGE Publications Inc.
- 802 [7] Graeme Blair, Jasper Cooper, Alexander Coppock, and Macartan Humphreys. Declaring and diagnosing research designs. *American Political Science  
 803 Review*, 113(3):838–859, 08 2019. doi: 10.1017/S0003055419000194. URL [https://www.cambridge.org/core/product/identifier/S0003055419000194/type/journal\\_article](https://www.cambridge.org/core/product/identifier/S0003055419000194/type/journal_article).
- 804 [8] Rotem Botvinik-Nezer, Felix Holzmeister, Colin F. Camerer, Anna Dreber, Juergen Huber, Magnus Johannesson, Michael Kirchler, Roni Iwanir,  
 805 Jeanette A. Mumford, R. Alison Adcock, Paolo Avesani, Blazej M. Baczkowski, Aahana Bajracharya, Leah Bakst, Sheryl Ball, Marco Barilaro, Nadège  
 806 Bault, Derek Beaton, Julia Beitner, Roland G. Benoit, Ruud M. W. J. Berkers, Jamil P. Banji, Bharat B. Biswal, Sebastian Bobadilla-Suarez, Tiago  
 807 Bortolini, Katherine L. Bottenhorn, Alexander Bowring, Senne Braem, Hayley R. Brooks, Emily G. Brudner, Cristian B. Calderon, Julia A. Camilleri,  
 808 Jaime J. Castrellon, Luca Cecchetti, Edna C. Cieslik, Zachary J. Cole, Olivier Collignon, Robert W. Cox, William A. Cunningham, Stefan Czoschke,  
 809 Kamalaker Dadi, Charles P. Davis, Alberto De Luca, Mauricio R. Delgado, Lysia Demetriou, Jeffrey B. Dennison, Xin Di, Erin W. Dickie, Ekaterina  
 810 Dobryakova, Claire L. Donnat, Juergen Dukart, Niall W. Duncan, Joke Durneze, Amr Eed, Simon B. Eickhoff, Andrew Erhart, Laura Fontanesi,  
 811 G. Matthew Fricke, Shiguang Fu, Adriana Galván, Remi Gau, Sarah Genon, Tristan Glatard, Enrico Glerean, Jelle J. Goeman, Sergej A. E. Golowin,  
 812 Carlos González-García, Krzysztof J. Gorgolewski, Cheryl L. Grady, Mikella A. Green, João F. Guassi Moreira, Olivia Guest, Shabnam Hakimi,  
 813 J. Paul Hamilton, Roeland Hancock, Giacomo Handjaras, Bronson B. Harry, Colin Hawco, Peer Herholz, Gabrielle Herman, Stephan Heunis, Felix  
 814 Hoffstaedter, Jeremy Hogeveen, Susan Holmes, Chuan-Peng Hu, Scott A. Huettel, Matthew E. Hughes, Vittorio Iacobella, Alexandru D. Iordan,  
 815 Peder M. Isager, Ayse I. Isik, Andrew Jahn, Matthew R. Johnson, Tom Johnstone, Michael J. E. Joseph, Anthony C. Juliano, Joseph W. Kable, Michalis  
 816 Kassinopoulos, Cemal Koba, Xiang-Zhen Kong, Timothy R. Koscik, Nuri Erkut Kucukboyaci, Brice A. Kuhl, Sebastian Kupek, Angela R. Laird,  
 817 Claus Lamm, Robert Langner, Nina Lauharatanahirun, Hongmi Lee, Sangil Lee, Alexander Leemans, Andrea Leo, Elise Lesage, Flora Li, Monica  
 818 Y. C. Li, Phui Cheng Lim, Evan N. Lintz, Schuyler W. Liphardt, Annabel B. Losecaat Vermeer, Bradley C. Love, Michael L. Mack, Norberto Malpica,  
 819 Theo Marins, Camille Maumet, Kelsey McDonald, Joseph T. McGuire, Helena Melero, Adriana S. Méndez Leal, Benjamin Meyer, Kristin N. Meyer,  
 820 Glad Mihai, Georgios D. Mitsis, Jorge Moll, Dylan M. Nielson, Gustav Nilsson, Michael P. Notter, Emanuele Olivetti, Adrian I. Onicas, Paolo  
 821 Papale, Kaustubh R. Patil, Jonathan E. Peelle, Alexandre Pérez, Doris Pischedda, Jean-Baptiste Poline, Yanina Prystauka, Shruti Ray, Patricia A.  
 822 Reuter-Lorenz, Richard C. Reynolds, Emiliano Ricciardi, Jenny R. Rieck, Anais M. Rodriguez-Thompson, Anthony Romyn, Taylor Salo, Gregory R.  
 823 Samanez-Larkin, Emilio Sanz-Morales, Margaret L. Schlichting, Douglas H. Schultz, Qiang Shen, Margaret A. Sheridan, Jennifer A. Silvers, Kenny  
 824 Skagerlund, Alec Smith, David V. Smith, Peter Sokol-Hessner, Simon R. Steinkamp, Sarah M. Tashjian, Bertrand Thirion, John N. Thorp, Gustav  
 825 Tinghög, Loreen Tisdall, Steven H. Tompson, Claudio Toro-Serey, Juan Jesus Torre Tresols, Leonardo Tozzi, Vuong Truong, Luca Turella, Anna E.  
 826 van 't Veer, Tom Verguts, Jean M. Vettel, Sagana Vijayarajah, Khoi Vo, Matthew B. Wall, Wouter D. Weeda, Susanne Weis, David J. White, David  
 827 Wisniewski, Alba Xifra-Porxas, Emily A. Yearling, Sangsuk Yoon, Rui Yuan, Kenneth S. L. Yuen, Lei Zhang, Xu Zhang, Joshua E. Zosky, Thomas E.  
 828 Nichols, Russell A. Poldrack, and Tom Schonberg. Variability in the analysis of a single neuroimaging dataset by many teams. *Nature*, 582(7810):  
 829 84–88, 06 2020. doi: 10.1038/s41586-020-2314-9. URL <https://www.nature.com/articles/s41586-020-2314-9>. Publisher: Nature Publishing Group.
- 830 [9] Susanne Breitner, Matthias Stözel, Josef Cyrys, Mike Pitz, Gabriele Wölke, Wolfgang Kreyling, Helmut Küchenhoff, Joachim Heinrich, H.-Erich  
 831 Wichmann, and Annette Peters. Short-term mortality rates during a decade of improved air quality in erfurt, germany. *Environmental Health  
 Perspectives*, 117(3):448–454, 03 2009. doi: 10.1289/ehp.11711. URL <https://ehp.niehs.nih.gov/doi/10.1289/ehp.11711>. Publisher: Environmental  
 832 Health Perspectives.

- [833] [10] Richard T. Burnett, Sabit Cakmak, Mark E. Raizenne, David Stieb, Renaud Vincent, Daniel Krewski, Jeffrey R. Brook, Owen Philips, and Haluk Ozkaynak. The association between ambient carbon monoxide levels and daily mortality in toronto, canada. *Journal of the Air & Waste Management Association*, 48(8):689–700, 08 1998. doi: 10.1080/10473289.1998.10463718. URL <https://www.tandfonline.com/doi/full/10.1080/10473289.1998.10463718>.
- [834] [11] Richard T. Burnett, Stieb ,Dave , Brook Jeffrey R. , Cakmak ,Sabit , Dales ,Robert , Raizenne ,Mark , Vincent ,Renaud , , and Tom Dann. Associations between short-term changes in nitrogen dioxide and mortality in canadian cities. *Archives of Environmental Health: An International Journal*, 59(5):228–236, 05 2004. doi: 10.3200/AEOH.59.5.228–236. URL <https://doi.org/10.3200/AEOH.59.5.228–236>. Publisher: Routledge \_eprint: <https://doi.org/10.3200/AEOH.59.5.228–236> PMID: 16201668.
- [835] [12] Margarita Castillejos, Borja-Aburto ,Victor H. , Dockery ,Douglas W. , Gold ,Diane R. , , and Dana Loomis. Airborne coarse particles and mortality. *Inhalation Toxicology*, 12(sup1):61–72, 01 2000. doi: 10.1080/0895-8378.1987.11463182. URL <https://doi.org/10.1080/0895-8378.1987.11463182>. Publisher: Taylor & Francis \_eprint: <https://doi.org/10.1080/0895-8378.1987.11463182>.
- [836] [13] Chaomei Chen. Citespac ii: Detecting and visualizing emerging trends and transient patterns in scientific literature. *Journal of the American Society for Information Science and Technology*, 57(3):359–377, 2006. doi: 10.1002/asi.20317. URL <https://onlinelibrary.wiley.com/doi/abs/10.1002/asi.20317>. \_eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/asi.20317>.
- [837] [14] J. K. Chou and C. K. Yang. Papervis: Literature review made easy. *Computer Graphics Forum*, 30(3):721–730, 2011. doi: 10.1111/j.1467-8659.2011.01921.x. URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-8659.2011.01921.x>. \_eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-8659.2011.01921.x>.
- [838] [15] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Naacl-hlt 2019. page 4171–4186, Minneapolis, Minnesota, 06 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1423. URL <https://aclanthology.org/N19-1423>.
- [839] [16] Douglas W. Dockery, Joel Schwartz, and John D. Spengler. Air pollution and daily mortality: Associations with particulates and acid aerosols. *Environmental Research*, 59(2):362–373, 12 1992. doi: 10.1016/S0013-9351(05)80042-8. URL <https://www.sciencedirect.com/science/article/pii/S0013935105800428>.
- [840] [17] Marian Dörk, Nathalie Henry Riche, Gonzalo Ramos, and Susan Dumais. Pivotpaths: Strolling through faceted information spaces. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2709–2718, 12 2012. doi: 10.1109/TVCG.2012.252. URL <https://ieeexplore.ieee.org/document/6327277>.
- [841] [18] Andrew Gelman and Eric Loken. The statistical crisis in science. *American Scientist*, 102(6):460–465, 12 2014. URL <https://www.proquest.com/docview/1616141998/abstract/5E050DCE82414037PQ/1>. Num Pages: 6 Place: Research Triangle Park, United States Publisher: Sigma XI-The Scientific Research Society.
- [842] [19] Elliot Gould, Hannah S. Fraser, Timothy H. Parker, Shinichi Nakagawa, Simon C. Griffith, Peter A. Vesk, Fiona Fidler, Daniel G. Hamilton, Robin N. Abbey-Lee, Jessica K. Abbott, Luis A. Aguirre, Carles Alcaraz, Irith Aloni, Drew Altschul, Kunal Arekar, Jeff W. Atkins, Joe Atkinson, Christopher M. Baker, Meghan Barrett, Kristian Bell, Suleiman Kehinde Bello, Iván Beltrán, Bernd J. Berauer, Michael Grant Bertram, Peter D. Billman, Charlie K. Blake, Shannon Blake, Louis Blairst, Andrea Bonisoli-Alquati, Timothée Bonnet, Camille Nina Marion Bordes, Aneesh P. H. Bose, Thomas Botterill-James, Melissa Anna Boyd, Sarah A. Boyle, Tom Bradfer-Lawrence, Jennifer Bradham, Jack A. Brand, Martin I. Brengdahl, Martin Bulla, Luc Bussière, Ettore Camerlenghi, Sara E. Campbell, Leonardo L. F. Campos, Anthony Caravaggi, Pedro Cardoso, Charles J. W. Carroll, Therese A. Catanach, Xuan Chen, Heung Ying Janet Chik, Emily Sarah Choy, Alec Philip Christie, Angela Chuang, Amanda J. Chunco, Bethany L. Clark, Andrea Contina, Garth A. Covernton, Murray P. Cox, Kimberly A. Cressman, Marco Crotti, Connor Davidson Crouch, Pietro B. D'Amelio, Alexandra Allison de Sousa, Timm Fabian Döbert, Ralph Dobler, Adam J. Dobson, Tim S. Doherty, Szymon Marian Drobniak, Alexandra Grace Duffy, Alison B. Duncan, Robert P. Dunn, Jamie Dunning, Trishna Dutta, Luke Eberhart-Hertel, Jared Alan Elmore, Mahmoud Medhat Elsherif, Holly M. English, David C. Ensminger, Ulrich Rainer Ernst, Stephen M. Ferguson, Esteban Fernandez-Juricic, Thalita Ferreira-Arruda, John Fieberg, Elizabeth A. Finch, Evan A. Fiorenza, David N. Fisher, Amélie Fontaine, Wolfgang Forstmeier, Yoan Fourcade, Graham S. Frank, Cathryn A. Freund, Eduardo Fuentes-Lillo, Sara L. Gandy, Dustin G. Gannon, Ana I. García-Cervigón, Alexis C. Garretson, Xuezhen Ge, William L. Geary, Charly Géron, Marc Gilles, Antje Girndt, Daniel Glikzman, Harrison B. Goldspiel, Dylan G. E. Gomes, Megan Kate Good, Sarah C. Goslee, J. Stephen Gosnell, Eliza M. Grames, Paolo Gratton, Nicholas M. Grebe, Skye M. Greenler, Maaike Griffioen, Daniel M. Griffith, Frances J. Griffith, Jake J. Grossman, Ali Güncan, Stef Haesen, James G. Hagan, Heather A. Hager, Jonathan Philo Harris, Natasha Dean Harrison, Sarah Syedia Hasnain, Justin Chase Havird, Andrew J. Heaton, María Laura Herrera-Chaustré, Tanner J. Howard, Bin-Yan Hsu, Fabiola Iannarilli, Esperanza C. Iranzo, Erik N. K. Iverson, Saheed Olaide Jimoh, Douglas H. Johnson, Martin Johnson, Jesse Jorna, Tommaso Jucker, Martin Jung, Ineta Kačergytė, Oliver Kaltz, Alison Ke, Clint D. Kelly, Katharine Keegan, Friedrich Wolfgang Keppeler, Alexander K. Killion, Dongmin Kim, David P. Kochan, Peter Korsten, Shan Kothari, Jonas Kuppler, Jillian M. Kusch, Małgorzata Lagisz, Kristen Marianne Lalla, Daniel J. Larkin, Courtney L. Larson, Katherine S. Lauck, M. Elise Lauterbur, Alan Law, Don-Jean Léandri-Breton, Jonas J. Lembrechts, Kiara L'Herpiniere, Eva J. P. Lievens, Daniela Oliveira de Lima, Shane Lindsay, Martin Luquet, Ross MacLeod, Kirsty H. Macphie, Kit Magellan, Magdalena M. Mair, Lisa E. Malm, Stefano Mammola, Caitlin P. Mandeville, Michael Manhart, Laura Milena Manrique-Garzon, Elina Mäntylä, Philippe Marchand, Benjamin Michael Marshall, Charles A. Martin, Dominic Andreas Martin, Jake Mitchell Martin, April Robin Martiniq, Erin S. McCallum, Mark McCauley, Sabrina M. McNew, Scott J. Meiners, Thomas Merkling, Marcus Michelangeli, Maria Moiron, Bruno Moreira, Jennifer Mortensen, Benjamin Mos, Taofeek Olatunbosun Muraina, Penelope Wrenn Murphy, Luca Nelli, Petri Niemelä, Josh Nightingale, Gustav Nilsson, Sergio Nolazco, Sabine S. Nooten, Jessie Lanterman Novotny, Agnes Birgitta Olin, Chris L. Organ, Kate L. Ostevik, Facundo Xavier Palacio, Matthieu Paquet, Darren James Parker, David J. Pascall, Valerie J. Pasquarella, John Harold Paterson, Ana Payo-Payo, Karen Marie Pedersen, Grégoire Perez, Kayla I. Perry, Patrice Pottier, Michael J. Proulx, Raphaël Proulx, Jessica L. Pruitt, Veronarindra Ramananjato, Finaritra Tolotra Randimbiarison, Onja H. Razafindratsima, Diana J. Rennison, Federico Riva, Sepand Riyahi, Michael James Roast,

- 885 Felipe Pereira Rocha, Dominique G. Roche, Cristian Román-Palacios, Michael S. Rosenberg, Jessica Ross, Freya E. Rowland, Deusdedith Rugemalila,  
 886 Avery L. Russell, Sivi Ruuskanen, Patrick Saccone, Asaf Sadeh, Stephen M. Salazar, Kris Sales, Pablo Salmón, Alfredo Sánchez-Tójar, Leticia Pereira  
 887 Santos, Francesca Santostefano, Hayden T. Schilling, Marcus Schmidt, Tim Schmoll, Adam C. Schneider, Allie E. Schrock, Julia Schroeder, Nicolas  
 888 Schtickzelle, Nick L. Schultz, Drew A. Scott, Michael Peter Scroggie, Julie Teresa Shapiro, Nitika Sharma, Caroline L. Shearer, Diego Simón, Michael I.  
 889 Sitvarin, Fabrício Luiz Skupien, Heather Lea Slinn, Grania Polly Smith, Jeremy A. Smith, Rahel Sollmann, Kaitlin Stack Whitney, Shannon Michael  
 890 Still, Erica F. Stuber, Guy F. Sutton, Ben Swallow, Conor Claverie Taff, Elina Takola, Andrew J. Tanentzap, Rocio Tarjuelo, Richard J. Telford,  
 891 Christopher J. Thawley, Hugo Thierry, Jacqueline Thomson, Svenja Tidau, Emily M. Tompkins, Claire Marie Tortorelli, Andrew Trlica, Biz R.  
 892 Turnell, Lara Urban, Stijn Van de Vondel, Jessica Eva Megan van der Wal, Jens Van Eckhoven, Francis van Oordt, K. Michelle Vanderwel, Mark C.  
 893 Vanderwel, Karen J. Vanderwolf, Juliana Vélez, Diana Carolina Vergara-Florez, Brian C. Verrelli, Marcus Vinícius Vieira, Nora Villamil, Valerio  
 894 Vitali, Julien Vollering, Jeffrey Walker, Xanthe J. Walker, Jonathan A. Walter, Paweł Waryszak, Ryan J. Weaver, Ronja E. M. Wedegärtner, Daniel L.  
 895 Weller, and Shannon Whelan. Same data, different analysts: variation in effect sizes due to analytical decisions in ecology and evolutionary biology.  
*BMC Biology*, 23(1):35, 02 2025. doi: 10.1186/s12915-024-02101-x. URL <https://doi.org/10.1186/s12915-024-02101-x>.
- [20] Florian Heimerl, Qi Han, Steffen Koch, and Thomas Ertl. Citerivers: Visual analytics of citation patterns. *IEEE Transactions on Visualization and Computer Graphics*, 22(1):190–199, 01 2016. doi: 10.1109/TVCG.2015.2467621. URL <https://ieeexplore.ieee.org/document/7192685/authors>.
- [21] Wei Huang, Jianguo Tan, Haidong Kan, Ni Zhao, Weimin Song, Guixiang Song, Guohai Chen, Lili Jiang, Cheng Jiang, Renjie Chen, and Bingheng Chen. Visibility, air quality and daily mortality in shanghai, china. *Science of The Total Environment*, 407(10):3295–3300, 05 2009. doi: 10.1016/j.scitotenv.2009.02.019. URL <https://linkinghub.elsevier.com/retrieve/pii/S004896970900165X>.
- [22] Nick Huntington-Klein, Andreu Arenas, Emily Beam, Marco Bertoni, Jeffrey R. Bloem, Pralhad Burli, Naibin Chen, Paul Grieco, Godwin Ekpe, Todd Pugatch, Martin Saavedra, and Yaniv Stopnitzky. The influence of hidden researcher decisions in applied microeconomics. *Economic Inquiry*, 59(3):944–960, 2021. doi: 10.1111/ecin.12992. URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/ecin.12992>. \_eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecin.12992>.
- [23] Petra Isenberg, Tobias Isenberg, Michael Sedlmair, Jian Chen, and Torsten Möller. Visualization as seen through its research paper keywords. *IEEE Transactions on Visualization and Computer Graphics*, 23(1):771–780, 01 2017. doi: 10.1109/TVCG.2016.2598827. URL <https://ieeexplore.ieee.org/document/7539364>.
- [24] Alex Kale, Matthew Kay, and Jessica Hullman. Decision-making under uncertainty in research synthesis: Designing for the garden of forking paths. *CHI '19*, page 1–14, New York, NY, USA, 05 2019. Association for Computing Machinery. doi: 10.1145/3290605.3300432. URL <https://dl.acm.org/doi/10.1145/3290605.3300432>.
- [25] Haidong Kan, Stephanie J. London, Guohai Chen, Yunhui Zhang, Guixiang Song, Naiqing Zhao, Lili Jiang, and Bingheng Chen. Differentiating the effects of fine and coarse particles on daily mortality in shanghai, china. *Environment International*, 33(3):376–384, 04 2007. doi: 10.1016/j.envint.2006.12.001. URL <https://www.sciencedirect.com/science/article/pii/S0160412006002108>.
- [26] Klea Katsouyanni, Giota Touloumi, Evangelia Samoli, Alexandros Gryparis, Alain Le Tertre, Yannis Monopolis, Giuseppe Rossi, Denis Zmirou, Ferran Ballester, Azedine Boumghar, Hugh Ross Anderson, Bogdan Wojtyniak, Anna Paldy, Rony Braunstein, Juha Pekkanen, Christian Schindler, and Joel Schwartz. Confounding and effect modification in the short-term effects of ambient particles on total mortality: Results from 29 european cities within the apeha project. *Epidemiology*, 12(5):521, 09 2001. URL [https://journals.lww.com/epidem/fulltext/2001/09000/confounding\\_and\\_effect\\_modification\\_in\\_the.11.aspx](https://journals.lww.com/epidem/fulltext/2001/09000/confounding_and_effect_modification_in_the.11.aspx).
- [27] Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jaewoo Kang. Biobert: a pre-trained biomedical language representation model for biomedical text mining. *Bioinformatics*, 36(4):1234–1240, 02 2020. doi: 10.1093/bioinformatics/btz682. URL <https://academic.oup.com/bioinformatics/article/36/4/1234/5566506>.
- [28] S. L. Lee, W. H. S. Wong, and Y. L. Lau. Association between air pollution and asthma admission among children in hong kong. *Clinical & Experimental Allergy*, 36(9):1138–1146, 2006. doi: 10.1111/j.1365-2222.2006.02555.x. URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2222.2006.02555.x>. \_eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-2222.2006.02555.x>.
- [29] Jiali Liu, Nadia Boukhelifa, and James R. Eagan. Understanding the Role of Alternatives in Data Analysis Practices. *IEEE Transactions on Visualization and Computer Graphics*, 26(1):66–76, January 2020. ISSN 1941-0506. doi: 10.1109/TVCG.2019.2934593. URL <https://ieeexplore.ieee.org/document/8805460/>.
- [30] Yang Liu, Tim Althoff, and Jeffrey Heer. Paths explored, paths omitted, paths obscured: Decision points & selective reporting in end-to-end data analysis. *CHI '20*, page 1–14, New York, NY, USA, 04 2020. Association for Computing Machinery. doi: 10.1145/3313831.3376533. URL <https://dl.acm.org/doi/10.1145/3313831.3376533>.
- [31] Yang Liu, Alex Kale, Tim Althoff, and Jeffrey Heer. Boba: Authoring and visualizing multiverse analyses. *IEEE Transactions on Visualization and Computer Graphics*, 27(2):1753–1763, 02 2021. doi: 10.1109/TVCG.2020.3028985. URL <https://ieeexplore.ieee.org/document/9216579/>.
- [32] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. doi: 10.48550/arXiv.1907.11692.
- [33] T F Mar, G A Norris, J Q Koenig, and T V Larson. Associations between air pollution and mortality in phoenix, 1995–1997. *Environmental Health Perspectives*, 108(4):347–353, 04 2000. doi: 10.1289/ehp.00108347. URL <https://ehp.niehs.nih.gov/doi/abs/10.1289/ehp.00108347>. Publisher: Environmental Health Perspectives.
- [34] Suresh H. Moolgavkar. Air pollution and hospital admissions for diseases of the circulatory system in three u.s. metropolitan areas. *Journal of the Air & Waste Management Association*, 50(7):1199–1206, 07 2000. doi: 10.1080/10473289.2000.10464162. URL <https://doi.org/10.1080/10473289.2000.10464162>.

- 937 Publisher: Taylor & Francis.
- 938 [35] Suresh H. Moolgavkar. Air pollution and daily mortality in two u.s. counties: Season-specific analyses and exposure-response relationships. *Inhalation Toxicology*, 15(9):877–907, 01 2003. doi: 10.1080/08958370390215767. URL <https://doi.org/10.1080/08958370390215767>. Publisher: Taylor &
- 939 Francis.
- 940 [36] Arpit Narechania, Alireza Karduni, Ryan Wesslen, and Emily Wall. Vitality: Promoting serendipitous discovery of academic literature with
- 941 transformers & visual analytics. *IEEE Transactions on Visualization and Computer Graphics*, 28(1):486–496, 01 2022. doi: 10.1109/TVCG.2021.3114820.
- 942 URL <https://ieeexplore.ieee.org/document/9552447>.
- 943 [37] Bart Ostro, Rachel Broadwin, Shelley Green, Wen-Ying Feng, and Michael Lipsett. Fine particulate air pollution and mortality in nine california
- 944 counties: Results from calfine. *Environmental Health Perspectives*, 114(1):29–33, 01 2006. doi: 10.1289/ehp.8335. URL <https://ehp.niehs.nih.gov/doi/10.1289/ehp.8335>. Publisher: Environmental Health Perspectives.
- 945 [38] Abhraneel Sarma, Alex Kale, Michael Moon, Nathan Taback, Fanny Chevalier, Jessica Hullman, and Matthew Kay. multiverse: Multiplexing
- 946 alternative data analyses in r notebooks (version 0.6.2). *OSF Preprints*, 2021. URL <https://github.com/MUCollective/multiverse>.
- 947 [39] Marko Sarstedt, Susanne J. Adler, Christian M. Ringle, Gyeongcheol Cho, Adamantios Diamantopoulos, Heungsun Hwang, and Benjamin D.
- 948 Liengaard. Same model, same data, but different outcomes: Evaluating the impact of method choices in structural equation modeling. *Journal of*
- 949 *Product Innovation Management*, 41(6):1100–1117, 2024. doi: 10.1111/jipm.12738. URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/jipm.12738>.
- 950 \_eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/jipm.12738>.
- 951 [40] Joel Schwartz. The distributed lag between air pollution and daily deaths. *Epidemiology*, 11(3):320–326, 2000. URL <https://www.jstor.org/stable/3703220>. Publisher: Lippincott Williams & Wilkins.
- 952 [41] R. Silberzahn, E. L. Uhlmann, D. P. Martin, P. Anselmi, F. Aust, E. Awtrey, Š. Bahnik, F. Bai, C. Barnard, E. Bonnier, R. Carlsson, F. Cheung,
- 953 G. Christensen, R. Clay, M. A. Craig, A. Dalla Rosa, L. Dam, M. H. Evans, I. Flores Cervantes, N. Fong, M. Gamez-Djokic, A. Glenz, S. Gordon-McKeon,
- 954 T. J. Heaton, K. Hederos, M. Heene, A. J. Hofelich Mohr, F. Högden, K. Hui, M. Johannesson, J. Kalodimos, E. Kaszubowski, D. M. Kennedy, R. Lei,
- 955 T. A. Lindsay, S. Liverani, C. R. Madan, D. Molden, E. Molleman, R. D. Morey, L. B. Mulder, B. R. Nijstad, N. G. Pope, B. Pope, J. M. Prenoveau, F. Rink,
- 956 E. Robusto, H. Roderique, A. Sandberg, E. Schlüter, F. D. Schönbrodt, M. F. Sherman, S. A. Sommer, K. Sotak, S. Spain, C. Spörlein, T. Stafford,
- 957 L. Stefanutti, S. Tauber, J. Ullrich, M. Vianello, E.-J. Wagenmakers, M. Witkowiak, S. Yoon, and B. A. Nosek. Many analysts, one data set: Making
- 958 transparent how variations in analytic choices affect results. *Advances in Methods and Practices in Psychological Science*, 1(3):337–356, 09 2018. doi:
- 959 10.1177/2515245917747646. URL <https://doi.org/10.1177/2515245917747646>. Publisher: SAGE Publications Inc.
- 960 [42] Jan Simson, Fiona Draxler, Samuel Mehr, and Christoph Kern. Preventing harmful data practices by using participatory input to navigate the
- 961 machine learning multiverse. CHI '25, page 1–30, New York, NY, USA, 04 2025. Association for Computing Machinery. doi: 10.1145/3706598.3713482.
- 962 URL <https://dl.acm.org/doi/10.1145/3706598.3713482>.
- 963 [43] Imad Tbahriti, Christine Chichester, Frédérique Lisacek, and Patrick Ruch. Using argumentation to retrieve articles with similar citations: An
- 964 inquiry into improving related articles search in the medline digital library. *International Journal of Medical Informatics*, 75(6):488–495, 06 2006. doi:
- 965 10.1016/j.ijmedinf.2005.06.007. URL <https://www.sciencedirect.com/science/article/pii/S1386505605000894>.
- 966 [44] Kayo Ueda, Nitta , Hiroshi , Ono , Masaji , , and Ayano Takeuchi. Estimating mortality effects of fine particulate matter in japan: A comparison of time-
- 967 series and case-crossover analyses. *Journal of the Air & Waste Management Association*, 59(10):1212–1218, 10 2009. doi: 10.3155/1047-3289.59.10.1212.
- 968 URL <https://doi.org/10.3155/1047-3289.59.10.1212>. Publisher: Taylor & Francis \_eprint: <https://doi.org/10.3155/1047-3289.59.10.1212>.
- 969 [45] Hadley Wickham. Tidy data. *Journal of Statistical Software*, 59:1–23, 09 2014. doi: 10.18637/jss.v059.i10. URL <https://doi.org/10.18637/jss.v059.i10>.
- 970 [46] Hadley Wickham, Joe Cheng, and Aaron Jacobs. *ellmer: Chat with Large Language Models*, 2025. URL <https://CRAN.R-project.org/package=ellmer>. R package version 0.1.1.
- 971 [47] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, and Quoc V. Le. Xlnet: Generalized autoregressive pretraining for
- 972 language understanding. doi: 10.48550/arXiv.1906.08237.
- 973
- 974
- 975
- 976
- 977
- 978
- 979
- 980
- 981
- 982
- 983
- 984
- 985
- 986
- 987
- 988