

1   **A LLM-based pipeline for understanding decision choices in data analysis from  
2   published literature**

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4   Decision choices, such as selecting the degree of freedom for a smoothing spline and the rationale behind them, are essential for  
5   interpreting results and understanding how uncertainty propagates through an analysis. Understanding how such choices are made and  
6   identifying common patterns in decisions can help junior researchers learn the field, while offering domain researchers a survey-like  
7   overview of current analysis practices. However, these decisions are rarely studied, as it is impractical to interview authors about all  
8   the alternatives considered during the work or to rerun the analysis under different options. In this work, We propose a workflow  
9   to automatically extract analytic decisions and their stated reasons from published literature using Large Language Models (Claude  
10   and Gemini). The pipeline also contributes to the calculation of paper similarity based on the semantic similarity of these extracted  
11   decisions and their reasons, and the visualization of papers using clustering algorithms. We apply this workflow to a set of studies on  
12   the effect of particulate matter on mortality and hospital admission, conducted by researchers worldwide, which naturally provide  
13   alteranative analyses of the same question. This approach enables large-scale, automated studies of decision-making practices in data  
14   analysis, providing an alternative to existing manual interview-based studies and small-scale ‘many analysts experiments’.

15   CCS Concepts: • **Applied computing** → *Document analysis*; • **Human-centered computing** → **Empirical studies in HCI**.

16   Additional Key Words and Phrases: Large language models

17   **ACM Reference Format:**

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20   **1 Introduction**

21   Decisions are made at every stage of data analysis: from initial data collection and pre-processing to modelling choices.  
22   Different decision choices can have a direct impact to the final results, which can lead to different interpretation and  
23   policy recommendations that follow. When independent analysts analyzing the same dataset even to answer the same  
24   research questions, through many-analysts experiments, they often arrive at markedly different conclusions [8, 19, 46].  
25   This variability in results can be attributed to the flexibility analysts have in making decisions throughout the data  
26   analysis process, which Gelman and Loken [18] describe as the “garden of forking paths”. When such flexibility is  
27   misused, data analysis can lead to p-hacking, selective reporting, inflated effect sizes, and other issues, undermining the  
28   quality and credibility of the findings.

29   [this is not okay — Multiple recommendations have been proposed to improve data analysis practices, such as  
30   pre-registration and multiverse analysis. Bayesian methods also offer a different paradigm to p-value driven inference  
31   for interpreting statistical evidence. Most empirical studies of data analysis practices focus on specially designed and  
32   simplified analysis scenarios. While informative, these setups may not adequately capture the complexity of the data

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53 analysis with significant policy implications. [In practice, studying the data analysis decisions with actual applications is  
54 challenging.] Analysts may no longer be available for interviews due to job changes, and even when they are, recalling  
55 the full set of decisions and thinking process made during the analysis is often infeasible. Moreover, only until the last  
56 decades, analysis scripts and reproducible materials were not commonly required by journals for publishing. – up till  
57 here]

58 In this work, we develop a tabular format to record analytical decisions in data analysis and automate the extraction  
59 of these decisions from published papers using large language models (Gemini and Claude). The workflow also include a  
60 component to calculate paper similarity based on both the decisions and the semantic similarity of their rationales, and  
61 use clustering methods to visualize papers according to distance based on decision similarity. We apply this workflow to  
62 a set of 56 air pollution modelling studies estimating the effect size of particulate matter (PM2.5 or PM10) on mortality  
63 and hospital admissions, typically modeled using Poisson generalised linear models (GLMs) or generalized additive  
64 models (GAMs). Analysis of the extracted decisions reveals common choices in this type of analysis (number of knots  
65 or degree of freedom for smoothing methods for time, temperature and humidity) and find three distinct clusters  
66 corresponding to different smoothing methods (LOESS, natural spline, and smoothing spline) used in European and U.S.  
67 studies, consistent with findings from the APHENNA project [28].  
68

69 In summary, the contribution of this work includes:

- 70 • A new approach to study data analysis decision choices through automatic extraction of decisions from scientific  
71 literature using LLMs,
- 72 • A method to construct paper similarities based on the decisions and the semantic similarity of their rationale,
- 73 • A shiny GUI tool for validation LLM outputs in this context, and
- 74 • A dataset of decisions and rationale, along with metadata, compiled from 62 studies in air pollution mortality  
75 modelling.

## 76 2 Related work

### 77 2.1 Decision-making in data analysis

78 Data analysis involves making choices at every step, from initial data collection, data pre-processing to model specification,  
79 and post-processing. Each decision represents a branching point where analysts choose a specific path to follow,  
80 and the vast number of possible choices analysts can take forms what Gelman and Loken [18] describe as the “garden  
81 of forking paths”. While researchers may hope their inferential results are robust to the specific path taken through  
82 the garden, in practice, different choices can lead to substantially different conclusions. This has been empirically  
83 demonstrated through “many analyst experiments”, where independent research groups analyze the same dataset to  
84 address the same research questions with their own chosen analytic approach. A classic example is Silberzahn et al.  
85 [46], where researchers reported an odds ratio from 0.89 to 2.93 for the effect of soccer players’ skin tone on the number  
86 of red cards awarded by referees. Similar variability has been observed in structural equation modeling [44], applied  
87 microeconomics [22], neuroimaging [8], and ecology and evolutionary biology [19].

88 Examples like above have rendered decision-making in data analysis as a subject to study in human computer  
89 interaction. To understand how analysts making decisions during data analysis and navigating the garden of forking  
90 path, researchers have conducted qualitative interviews with analysts on data analysis practices [2, 24, 31]. Visualization  
91 tools have also been explored to communicate the decision process through analytic decision graphics (ADG) [32]. In  
92 fairness machine learning literature, Simson et al. [47] contributed a reusable workflow that supports participatory input  
93 and analysis.

105 to democratize decisions in machine learning algorithms related to fairness, privacy, interpretability and performance.  
106 Conducting qualitative studies through interviews to study how assumptions and decisions are made in data analysis  
107 practices takes a significant amount of time and effort, and the findings may not generalize to other contexts. While  
108 published research papers may not provide a complete picture of the decision-making process, they do contain valuable  
109 information about the choices made by analysts and the rationale behind them. With recent advances in Large Language  
110 Models (LLMs), it has become possible to automatically extract structured information from unstructured text. This  
111 could provide a scalable way to study decision-making practices in data analysis.  
112

113 On top of qualitative studies, software tools have also developed to incorporate potential alternatives in the analysis  
114 workflow. The `DeclareDesign` package [7] introduces the MIDA framework for researchers to declare, diagnose, and  
115 redesign their analyses to produce a distribution of the statistic of interest, which has been applied in the randomized  
116 controlled trial study [6]. The `multiverse` package [33, 43] provides a framework for researchers to conduct multiverse  
117 analysis to systematically explore how different choices affect results and to report the range of plausible outcomes that  
118 arise from alternative analytic paths.  
119

## 120 2.2 Visualization on scientific literature

121 With the growing volume of scientific publications and the difficulty of navigating the literature to stay informed,  
122 there is increasing interest in developing tools to visualize and recommend scientific papers. These systems link papers  
123 based on their similarity and relevance, typically determined by keywords [23], citation information (e.g. citation list,  
124 co-citation) [13], or combinations with other relevant paper metadata (e.g. author, title) [5, 14, 17, 20]. Recent approaches  
125 incorporate text-based information using topic modelling [1], argumentation-based information retrieval [48], and  
126 text embedding [39]. While metadata and high-level text-based information are useful for finding relevant papers,  
127 researchers also need tools that help them *make sense* of the literature rather than simply *locating* it. In applied data  
128 analysis, one interest is to understand how studies differ or align in their analytical approaches. Capturing the decisions  
129 and reasoning expressed in analyses on a shared theme enables the calculation of similarity metrics based on these  
130 choice and their underlying rationale, which supports clustering and visualizing paper to identify common practices in  
131 the field.  
132

## 133 3 Methods

134 TODO: a generic summary of the workflow, maybe an illustration  
135

### 136 3.1 Record decisions in data analysis

137 Consider the following excerpt from Ostro et al. [40] that describes the modelling approach to provide evidence of an  
138 association between daily counts of mortality and ambient particulate matter (PM10):  
139

140 Based on previous findings reported in the literature (e.g., Samet et al. 2000), the basic model included a  
141 smoothing spline for time with 7 degrees of freedom (df) per year of data. This number of degrees of  
142 freedom controls well for seasonal patterns in mortality and reduces and often eliminates autocorrelation.  
143

144 This sentence encode the following components of a decision:  
145

- 146 • **variable:** time
- 147 • **method:** smoothing spline
- 148 • **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

To record these decisions in a tabular format, we follow the tidy data principle [51], which states each variable should be in a column and each observation in a row. For our purpose, each row represents a decision made by the authors in 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. The decision choice above is a parameter choice of a statistical method applied to the variable. Analyses also include other types of decisions, such as temporal and spatial treatments, for example, the choice of lagged exposure for certain variables or whether the model is estimated collectively or separated for individual locations. These decisions don't have a specific method or parameter, but should still be recorded with the variable, type (spatial or temporal), reason, and decision fields.

Given the writing style and the quality of the analysis itself, multiple decisions may be combined in one sentence and certain fields, e.g. decision and reason, may be omitted. Consider the following excerpt from Ostro et al. [40]:

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

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

Paper	ID	variable	method	parameter	type	reason	decision
ostro	1	temperature	smoothing spline	degree of freedom	parameter	3 degree of freedom	NA
ostro	2	relative humidity	smoothing spline	degree of freedom	parameter	3 degree of freedom	NA
ostro	3	temperature	NA	NA	temporal	1-day lags	NA
ostro	4	relative humidity	NA	NA	temporal	1-day lags	NA

Notice in the example above, the reason field are recorded as NA. This is because the stated rationale ("and are likely to vary over time in concert with air pollution levels") only supports the general inclusion of temporal lags but does not justify the specific choice of 1-day lag over other alternatives, for example, 2-day average of lags 0 and 1 and single-day lag of 2 days. Similar scenario can happen when a direct decision is missing while a reason is provided ("done by minimizing Akaike's information criterion"), as in Katsouyanni et al. [27]:

The inclusion of lagged weather variables and the choice of smoothing parameters for all of the weather variables were done by minimizing Akaike's information criterion.

### 3.2 Extract decisions automatically from literature with LLMs

Manually extracting decisions from published papers is labor-intensive and time-consuming. With Large Language Models (LLMs), it has become possible to automatically extract structured information from unstructured text by supplying a set of PDF documents and a prompt for instruction. Text recognition from PDF document relies on Optical Manuscript submitted to ACM

209 Character Recognition (OCR) to convert scanned images into machine-readable text – capability currently offered by  
210 Anthropic Claude and Google Gemini. In the prompt, we assign the LLM a role as an applied statistician and instruct it  
211 to generate a markdown file containing a JSON block that extract decisions from the PDF in the format described in  
212 Section 3.1. We also provide a set of instructions and examples on the potential missing of reason and decision fields.  
213 Prompt engineering techniques [12, 54] are used to optimize the prompt script. The full prompt feed to the LLM is  
214 provided in the Appendix. We use the `chat_PROVIDER()` functions from the `ellmer` package [53] in R to obtain the  
215 output with Gemini and Claude API.  
216  
217

### 219 3.3 Validate and standardize LLM outputs

220 The LLM outputs need to be validated and standardized before further analysis. Validation focuses on ensuring the  
221 correctness of the extracted decisions by LLMs, while standardization aims to ensure consistency in variable and model  
222 names across papers, given authors may express the same concept in different ways. For example, “mean temperature”,  
223 “average temperature”, and “temperature” all refer to the same variable, which can be all standardized to “temperature”  
224 for consistency. To help with the validation and standardization process, we developed a Shiny application that provides  
225 an interactive interface for users to review and edit the LLM outputs. A Shiny application takes a CSV of extracted  
226 decisions as input and allows three types of edits: 1) *overwrite* – modify the content of a particular cell, 2) *delete* –  
227 remove a particular irrelevant decision, and 3) *add* – manually enter a missing decision. Figure 1 illustrates the *overwrite*  
228 action for standardizing the variable NCtot (The number concentration of urban background particles <100 nm in  
229 diameter) to “pollution”: the user enters a predicate function in the filter condition box on the left panel, and the filtered  
230 data will appear interactively in the right panel. The user can then specify the variable to overwrite and the new value  
231 and the corresponding cells in the right panel will be updated. This change need to be confirmed by pressing the “Apply  
232 changes” button to update the full dataset. The corresponding `tidyverse` [52] code will then be generated in the left  
233 panel to be included in an R script, and the edited table can be downloaded for future analysis.  
234  
235

### 236 3.4 Calculate paper similarity and visualization

237 Once the output has been extracted and validated, the decisions can be treated as data for further analysis. In this  
238 section, we construct a distance metric between pairs of papers based on the similarity of their decision choices. This  
239 metric can then be used as a distance matrix among papers for clustering, dimension reduction, and visualization.

240 For each paper pair, a decision is considered comparable if the papers share the same variable and decision type, for  
241 example, a parameter decision on temperature or the temporal decision on humidity. For two decisions to be considered  
242 similar, both the decision choice and the rationale are taken into account. A similar choice indicates a similar final  
243 decisions are made in the analysis, whereas a similar reason reflects a shared rationale or justification for the choice,  
244 even when the choices themselves differ, potentially due to differences in the underlying data. To assign numerical  
245 value for measuring the similarity, we use the semantic similarity from text model, using the `text` package [29]. We  
246 first obtain the text embedding for all the reason and decisions and calculate the cosine similarity between the matched  
247 reason and decisions. For parameter type decisions, the statistical method used also contributes to the similarity of the  
248 decision. Since semantic similarity cannot fully capture the difference betweenit statistical methods (the difference  
249 between smoothing spline and natural spline is not well represented by the textual difference of “smoothing” and  
250 “natural”), method similarity is encoded as binary: 1 if the two papers used the same method, and 0 otherwise. The  
251 paper similarity is then computed as the average similarity across all the matched methods, decisions, and reasons. The  
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**Edit decision table output**

Upload CSV  
Browse... gemini\_raw.csv  
Upload complete  
Overwrite Delete Add  
Filter condition (e.g., variable == 'PM10')  
The variable to overwrite  
The value modified to  
Apply changes Confirm  
Download CSV  
Generated tidyverse code  
df %>%  
d1 %>%  
mutate(variable = ifelse(paper == "andersen2008size" & id %in% "pollutant", "variable")) %>%

**Initial view**

paper	id	model	variable	method	parameter	type	reason	decision
andersen2008size	1	generalized additive Poisson time series regression model	temperature	smoothing spline	degrees of freedom	parameter	NA	4 or 5 df
andersen2008size	2	generalized additive Poisson time series regression model	dew-point temperature	smoothing spline	degrees of freedom	parameter	NA	4 or 5 df
andersen2008size	3	generalized additive Poisson time series regression model	calendar time	smoothing spline	degrees of freedom	parameter	to control for long-term trend and seasonality	3, 4, or 5 df/year
andersen2008size	4	generalized additive Poisson time series regression model	NCtot	NA	NA	temporal	to include days with the strongest lag effects	4-day pollutant average (lag 0-3)
andersen2008size	5	generalized additive Poisson time series regression model	NCtot	NA	NA	temporal	to include days with the strongest lag effects	5-day average (lag 0-4)
andersen2008size	6	generalized additive Poisson time series regression model	NCtot	NA	NA	temporal	to include days with the strongest lag effects	6-day average (lag 0-5)

**Edit decision table output**

Upload CSV  
Browse... gemini\_raw.csv  
Upload complete  
Overwrite Delete Add  
Filter condition (e.g., variable == 'PM10')  
paper == "andersen2008size" & id %in% 4:6  
The variable to overwrite  
variable  
The value modified to  
pollutant  
Apply changes Confirm  
Download CSV  
Generated tidyverse code  
df %>%  
d1 %>%  
mutate(variable = ifelse(paper == "andersen2008size" & id %in% "pollutant", "variable")) %>%

**Upon pressing the "Apply changes" button, the data panel will update to reflect the edit**

paper	id	model	variable	method	parameter	type	reason	decision	reference
andersen2008size	1	Generalized additive Poisson time series regression model	pollutant	NA	NA	temporal	to include days with the strongest lag effects	4-day pollutant average (lag 0-3)	NA
andersen2008size	5	Generalized additive Poisson time series regression model	pollutant	NA	NA	temporal	to include days with the strongest lag effects	5-day average (lag 0-4)	NA
andersen2008size	6	Generalized additive Poisson time series regression model	pollutant	NA	NA	temporal	to include days with the strongest lag effects	6-day average (lag 0-5)	NA

**Edit decision table output**

Upload CSV  
Browse... gemini\_raw.csv  
Upload complete  
Overwrite Delete Add  
Filter condition (e.g., variable == 'PM10')  
The variable to overwrite  
The value modified to  
Apply changes Confirm  
Download CSV  
Generated tidyverse code  
df %>%  
d1 %>%  
mutate(variable = ifelse(paper == "andersen2008size" & id %in% "pollutant", "variable")) %>%

**Upon confirmation, the changes will be applied to the full dataset**

paper	id	model	variable	method	parameter	type	reason	decision
andersen2008size	1	generalized additive Poisson time series regression model	temperature	smoothing spline	degrees of freedom	parameter	NA	4 or 5 df
andersen2008size	2	generalized additive Poisson time series regression model	dew-point temperature	smoothing spline	degrees of freedom	parameter	NA	4 or 5 df
andersen2008size	3	generalized additive Poisson time series regression model	calendar time	smoothing spline	degrees of freedom	parameter	to control for long-term trend and seasonality	3, 4, or 5 df/year
andersen2008size	4	generalized additive Poisson time series regression model	pollutant	NA	NA	temporal	to include days with the strongest lag effects	4-day pollutant average (lag 0-3)
andersen2008size	5	generalized additive Poisson time series regression model	pollutant	NA	NA	temporal	to include days with the strongest lag effects	5-day average (lag 0-4)
andersen2008size	6	generalized additive Poisson time series regression model	pollutant	NA	NA	temporal	to include days with the strongest lag effects	6-day average (lag 0-5)

Fig. 1. The Shiny application interface to validate and standardize Large Language Model (LLM)-generated output. (1) the default interface after loading the input CSV file. (2) The table view will update interactively to reflect the edit: for paper with handle “andersen2008size” and id in 4, 5, 6, replace the variable NCtot with “pollutant”. (3) After clicking the Confirm button, the corresponding tidyverse code is generated, and the table view returns to its original unfiltered view with the edits applied. The edited data can be downloaded by clicking the Download CSV button.

313 resulting paper similarity metric can be interpreted as a distance measure to cluster and visualize papers based on their  
 314 decision choices.  
 315

316 Because analyses vary in the decisions they report, the number of matched decisions differs across paper pairs. In  
 317 practice, some studies may not fully report the decision and reason for every choice made, leading to missing data for  
 318 the matched decisions. Although paper similarity can be calculated based on all available matched decisions, care  
 319 should be taken for pairs with only a small number of matches, as the paper similarity may be overly influenced by one  
 320 or two decisions. To address this, users may focus on a set of decisions shared across papers and on papers that report a  
 321 minimal number of these decisions when calculating paper similarity.  
 322

## 323 4 Results

324 In the study of the health effects of outdoor air pollution, one area of interest is the association between short-term,  
 325 day-to-day changes in particulate matter air pollution and daily mortality counts. This question has been studied  
 326 extensively by researchers across the globe and in the US, it serves to provide scientific evidence for to guide public policy  
 327 on setting the National Ambient Air Quality Standards (NAAQS) for air pollutants. While individual modelling choices  
 328 vary, these studies often share a common structure: they adjust for meteorological covariates such as temperature and  
 329 humidity, apply temporal or spatial treatments, like including lagged variables and may estimate the effect by city or  
 330 region before combining results. This naturally forms a “many-analyst” experiment setting where different researchers  
 331 analyze similar data to address the same scientific question and the analyses are documented in published papers.  
 332

333 From the 56 studies examining the effect of particulate matters ( $PM_{10}$  and  $PM_{2.5}$ ) on mortality and hospital admission,  
 334 we focus on the baseline model reported in each paper, excluding secondary models (e.g. lag-distributed models) and  
 335 sensitivity analysis. We also exclude decisions on other pollutants, such as nitrogen dioxide ( $NO_2$ ). This yields 242  
 336 decisions extracted using Gemini, averaging approximately 4 decisions per paper.  
 337

### 338 4.1 Validation and standardization of LLM outputs

339 Table 2. Summary of validation and standardization edits made during the review process.  
 340

341 Reason	342 Count
343 Remove decisions out of scope: other pollutants and sensitivity analysis	344 50
345 Edit made to recode smoothing parameter unit to per year	346 45
347 Duplicates	348 9
349 Fix incorrect capture	350 9
351 Edit made due to decisions are too general, e.g. minimum of 1 df per year was required	352 6
353 Remove decisions related to definition of variables, e.g. season	354 5
355 Total	356 124

357 Table 2 summarizes the number of edits made during the review process using the Shiny application. These edits  
 358 fall into two main categories: 1) correcting LLM outputs and 2) standardizing extracted decision. The first category  
 359 includes fixing incorrect captures, removing non-decision (e.g. definition of variables), removing duplication, excluding  
 360 irrelevant decisions (e.g. sensitivity analyses), and excluding decisions whose stated reasons reflect general guidelines  
 361 rather than actual choices (e.g. “minimum of 1 degree of freedom per year is required”).  
 362

365 Table 3. Missingness of decision and reason fields in the Gemini-extracted decisions. Most decisions report the choice (35.5 + 57.1 =  
 366 92%), but 57.1% lacks a stated reason.

Reason	Decision	
	Non-missing	Missing
Non-missing	90 (37.2%)	14 (5.8%)
Missing	134 (55.4%)	4 (1.7%)

374 Standardization addresses variation in how authors express variable names and decisions. For example, variable  
 375 names such as “mean temperature” and “average temperature” refer to the same variable and should be aligned for  
 376 comparison for later decision similarity calculation. Variable names are manually standardized into four main categories:

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

381 Notice that “dewpoint temperature” is standardized under humidity because it serves as a proxy for temperature in  
 382 achieving a 100% relative humidity.

383 Decisions themselves also require standardization. For example, the smoothing parameter (number of knots and  
 384 degree of freedom) may be expressed *per year* or *in total*, and temporal lag decision may be expressed in different  
 385 formats (e.g. “6-day average”, “mean of lags 0+1”, “lagged exposure up to 6 days”). Smoothing parameter units are  
 386 manually recoded to a *per year* basis for consistency, as reflected in Table 2. Temporal decision show a wider variety,  
 387 generally falling into two categories:

- 388 • **multi-day average lags**, such as “6-day average”, “3-d moving average”, “mean of lags 0+1”, “cumulative lags,  
 389 mean 0+1+2” and
- 390 • **single-day lags**, such as “lagged exposure up to 6 days”, “lag days from 0 to 5”.

391 This variability makes manual standardization impractical, hence we apply a secondary LLM process (claude-3-  
 392 7-sonnet-latest) using the ellmer package to convert temporal decisions into a consistent format: multi-day: lag  
 393 [start]-[end] and single-day: lag [start], . . . , lag [end]. For instance, “6-day average” is converted to  
 394 “multi-day: lag 0-5” and “lagged exposure up to 6 days” is converted to “single-day: lag 0, lag 1, lag 2, lag 3, lag 4, lag 5”.

## 403 4.2 Exploratory analysis of decision choices

404 As raised in Section 3.1, not all decisions reported in the literature include both the decision choice and the rationale.  
 405 Some decisions may only report the choice without a stated reason, while others may provide a reason without  
 406 specifying the exact choice made. Table 3 summarizes the missingness of the decisions and reason for the extracted  
 407 decisions. While 2% of decisions are complete for both decision and reasons, 55% of decisions lack a stated rationale  
 408 for the choice. This reflects a common reporting practice in the field, where authors often present the decision itself  
 409 without providing a justification, e.g. “We decide to use  $x$  degree of freedom for variable  $y_1$  and  $y_2$ ”. This also includes  
 410 cases where authors provide general guidelines for selecting the parameter, but the rationale is too broad to justify the  
 411 specific choice made (hence validated as NA in Section 4.1).

417 Table 4. Count of variable-type decisions in the Gemini-extracted decisions. The most commonly reported decision are the parameter  
 418 choices and temporal lags for time, PM, temperature, and humidity.

Variable	Type	Count
time	parameter	44
PM	temporal	39
temperature	parameter	35
humidity	parameter	25
temperature	temporal	23
humidity	temporal	19
PM	parameter	9
time	temporal	3

433 Table 4 lists the eight most frequently reported decision: parameter and temporal choice for time, PM, temperature,  
 434 and humidity. While a wider list of variables have been used in the analysis, these four variables are most commonly  
 435 included in baseline models. Parameter choices for time, temperature, and humidity are typically made on the use of  
 436 smoothing parameter for the smoothing method (natural spline and smoothing spline), whereas temporal choices are  
 437 commonly reported for PM, temperature, and humidity for the number of lag to consider in the model.  
 438

440 Table 5. Options captured for parameter choices for time, humidity, and temperature variables in the Gemini-extracted decisions.  
 441 The choices for natural spline knots are generally less varied than the degree of freedom choices for smoothing spline. Choices for  
 442 temperature and humidity tend to be close, given they are both weather related variables, while the choices for time are more varied  
 443 inherently.

Method	Variable	Decision
natural spline	humidity	3, 4
natural spline	temperature	3, 4, 6
natural spline	time	1, 1.5, 3, 4, 6, 7, 8, 12, 15, 30
smoothing spline	humidity	2, 3, 4, 6, 8, 50% of the data
smoothing spline	temperature	2, 3, 4, 6, 8, 50% of the data
smoothing spline	time	1, 3, 4, 5, 6, 7, 7.7, 8, 9, 10, 12, 30, 100, 5% of the data

456 Table 5 presents the parameter-related decisions extracted for spline methods (natural and smoothing spline) applied  
 457 to variable time, humidity and temperature. These decisions concern the number of knots or degree of freedom, with all  
 458 values standardized to a *per year* scale for consistency. The selection of knot for natural spline has less variation than  
 459 the degree of freedom choices for smoothing spline. Choices for temperature and humidity are generally similar, given  
 460 they are both weather related variables, whereas choices for time are more varied. This tabulation provides a reference  
 461 set for common parameter choices for future studies and help to identify anomalies and special treatment in practice.  
 462 For example, the choice of 7.7 degree of freedom reported in Castillejos et al. [11] may prompt analysts to seek further  
 463 justification. By cross comparing with other reporting, some decisions appear ambiguous. For example, in Moolgavkar  
 464 [37] and Moolgavkar [38], the reported value of 30 and 100 degrees of freedom for time may be understandable for  
 465

469 experienced domain researcher, it could be unclear for junior analysts as to whether they apply to the full 9 year period  
 470 or on a per-year basis. We also observe a different report style from Schwartz [45], where smoothing spline parameters  
 471 are expressed as a proportion of the data (“5% of the data” and “5% of the data”) rather than fixed numerical value.  
 472

473 Table 6. Options captured for temporal lag choices for PM, temperature, and humidity variables in the Gemini-extracted decisions.  
 474 Both single-day lags and multi-day average lags are commonly used, generally considering up to five days prior (lag 5).  
 475

Lag type	Variable	Decision
multi-day average	PM	lag 0-1, 0-2, 0-3, 0-4, 0-5, 0-6
multi-day average	humidity	lag 0-1, 0-2, 0-3, 0-5, 1-5, 2-4
multi-day average	temperature	lag 0-1, 0-2, 0-3, 0-5, 2-4
single-day lag	PM	lag 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13
single-day lag	humidity	lag 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13
single-day lag	temperature	lag 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13

476 Similarly, Table 6 summarizes the temporal lag choices for PM, temperature, and humidity. For single-day lags, the  
 477 lags are considered up to 13 days (approximately two weeks). For multi-day averages, 3-day and 5-day averages are  
 478 most common, although other choices such as 2-4 day average are also observed as in López-Villarrubia et al. [35]:  
 479

480 In particular, lags 0 to 1 and lags 2 to 4 averages of temperature, relative humidity, and barometric  
 481 pressure were considered as meteorological variables.  
 482

### 483 4.3 Paper similarity and clustering

484 Given the number of decisions reported in Table 4, we focus on the six most common variable-type decisions for  
 485 calculating paper similarity: parameter choices for time, temperature, and humidity, and temporal lag choices for PM,  
 486 temperature, and humidity. We also restrict our analysis to papers that report at least three of these six decisions, resulting  
 487 in 48 papers for the similarity analysis. This ensures that the paper similarity metric is based on a sufficient number of  
 488 comparable decisions. We use the default text embedding model (BERT) in the text package and cosine similarity to  
 489 compute the similarity score. Sensitivity analysis on different text embedding model is checked in Section 4.4.3. Paper  
 490 similarity is then calculated as the average of decision similarity for each paper pair. The resulting distance matrix  
 491 is then used for hierarchical clustering in Figure 2 and multi-dimensional scaling (MDS) in Figure 3. The two MDS  
 492 dimension reveals three clusters correspond to the three smoothing methods used in these analyses: LOESS, natural  
 493 spline, and smoothing spline. This grouping aligns with the modelling strategies seen in large-scale analysis, such as  
 494 the U.S. NMMAPS study [42] and the European APHEA [26] and APHEA2 [27] project.  
 495

496 To reconcile these differences, the APHENA project [28] was launched with the aim to “assess the consistency across  
 497 Europe and North America when estimated using a common analytic protocol and to explore possible explanations for  
 498 any remaining variation”. While multi-dimensional scaling in Figure 3 shows the match of three clusters with three  
 499 smoothing methods, this is not inconsistent with the APHENA project [28] that the amount of smoothing to have a  
 500 more important role than the method of smoothing for estimating the effect of PM on public health variables. The  
 501 similarity metric we proposed focuses on the variation of choices across analyses, without directly assessing how those  
 502 choices influence results. By pooling decision choices from multiple studies with LLMs, it becomes much easier to  
 503 reveal common practices and difference in research practices, highlighting decisions that require further sensitivity  
 504

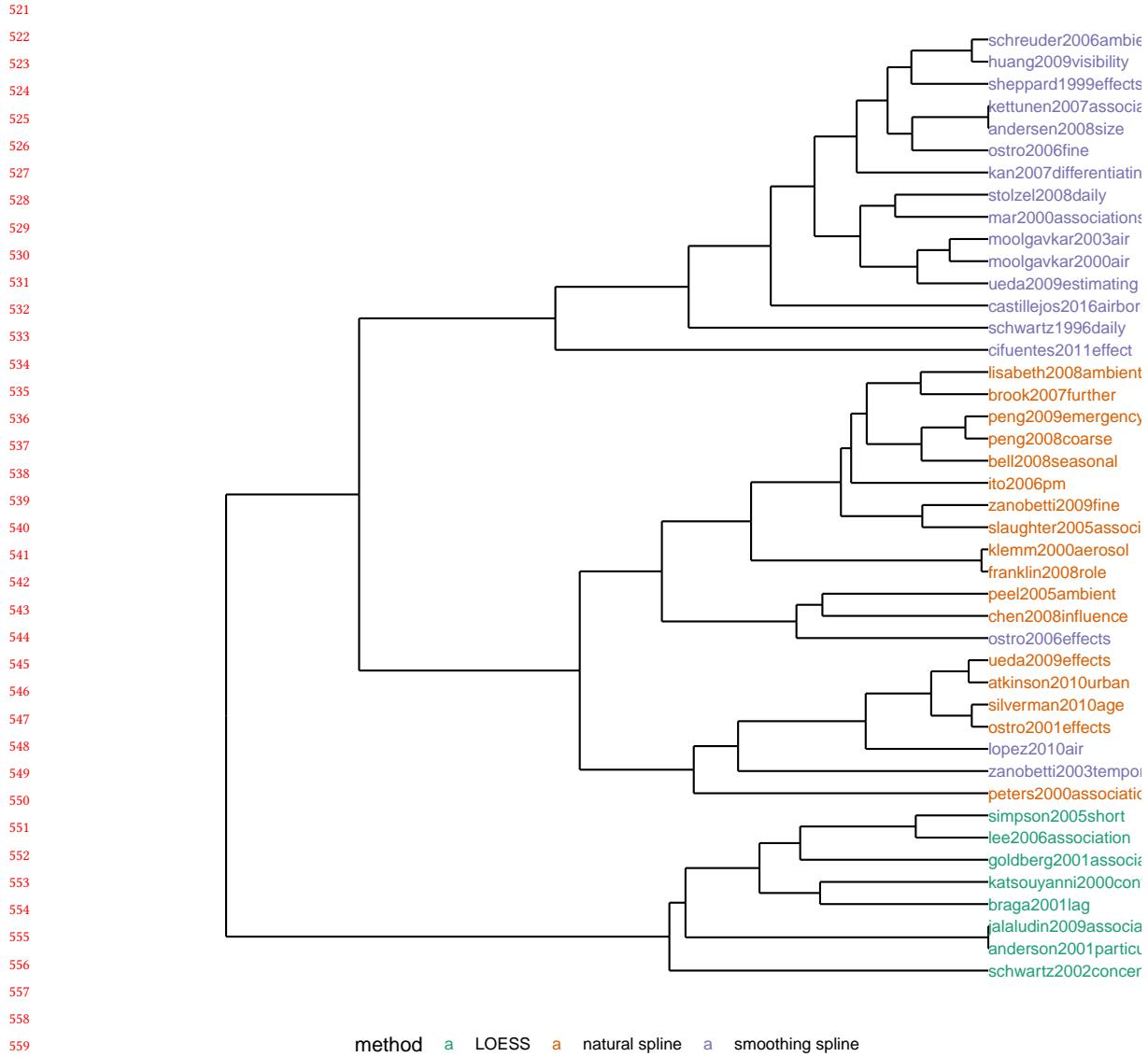


Fig. 2. Maybe we don't need the hierarchical clustering plot because it has the same information as the next MDS one???

analyses to assess their impact. The different smoothing methods revealed in Figure 3 are consistent with the analysis by Peng et al. [41] and Touloumi et al. [49] that compares different smoothing methods and rationale for selecting smoothing parameters.

#### 4.4 Sensitivity analysis

A series of sensitivity analysis has been conducted to explore the reproducibility for using LLMs for text extraction tasks (Section 4.4.1), discrepancies in decision extraction between different LLM models: Gemini (gemini-2.0-flash)

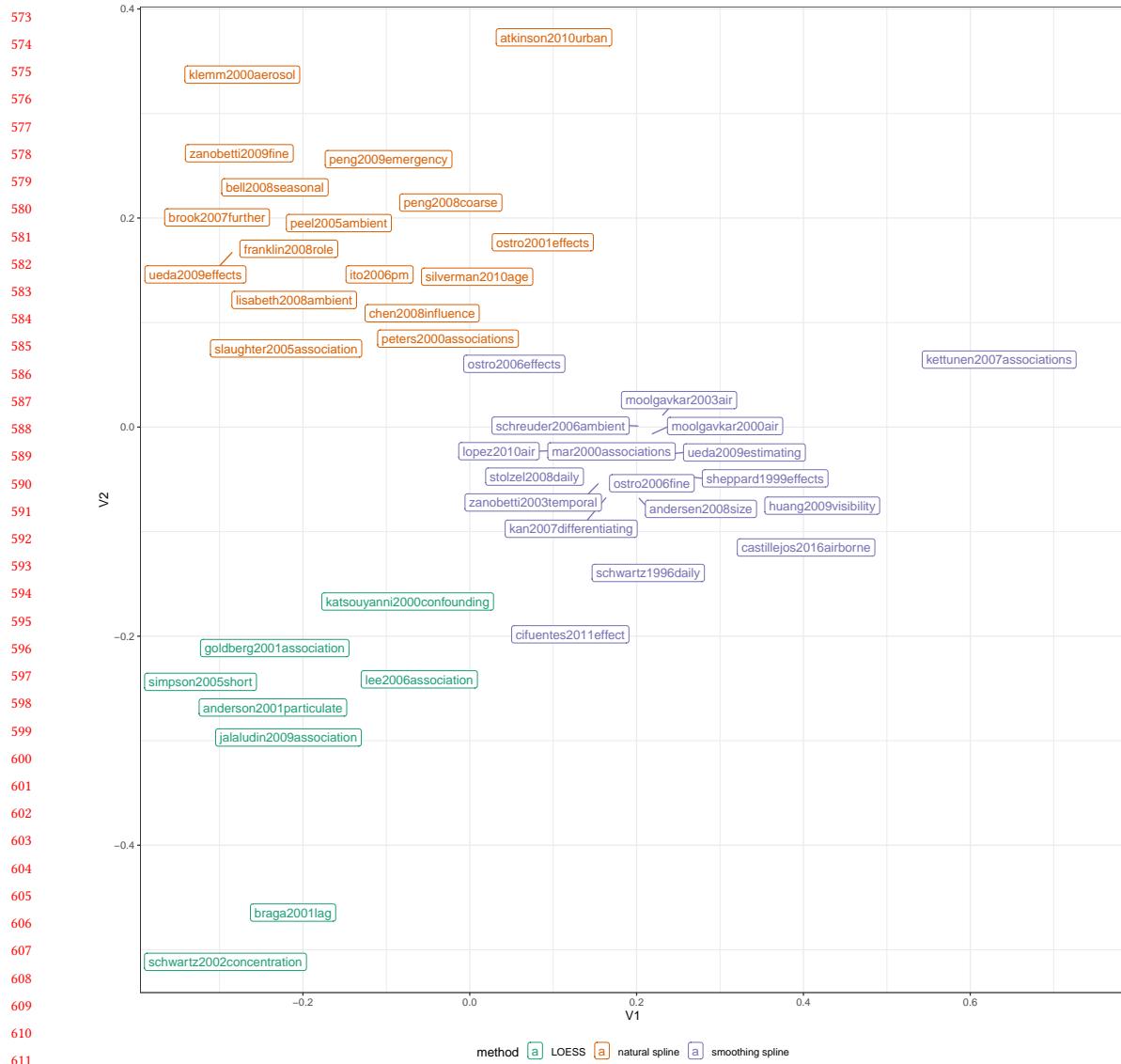


Fig. 3. The multi-dimensional scaling (MDS) based on paper similarity distance for `length(good_pp)` air pollution mortality modelling papers, colored by the smoothing method used. The MDS reveals the three distinct groups of papers, corresponds to LOESS, natural spline, and smoothing spline. These groups corresponds to the different modelling strategies debated in the European and U.S. studies, as documented in the APHENNA project [28].

and Claude (`claude-3-7-sonnet-latest`) (Section 4.4.2), and the sensitivity of text model for computing the semantic decision similarity (Section 4.4.3).

**4.4.1 LLM reproducibility.** We assess the reproducibility of Gemini’s text extraction (`gemini-2.0-flash`) by repeating the task five times for each of the 62 papers and perform pairwise comparison between runs. This generates  $5 \times 4 / 2 \times 62 =$  Manuscript submitted to ACM

620 possible comparisons for both “reason” and “decisions” fields. Comparisons where the runs produced a different  
 626 number of decisions were excluded, as this would require manual alignment. After filtering, 449 out of 620 (72%)  
 627 remained. Table 7 prints the decisions in Andersen et al. [3] across two runs and all the four decisions are identical with  
 628 no difference.

630  
 631 Table 7. Example comparing Gemini’s text extraction for Andersen et al. [3] across two runs. The extracted decisions are identical in  
 632 both runs.

Variable	Run1	Run2
NCtot	6day average (lag 05)	6day average (lag 05)
calendar time	3 4 or 5 dfyear	3 4 or 5 dfyear
dew-point temperature	4 or 5 df	4 or 5 df
temperature	4 or 5 df	4 or 5 df

641  
 642 Table 8. Number of differences in the reason and decision fields across Gemini runs for papers with consistent number of decisions  
 643 across runs.

Num. of difference	Count	Proportion (%)
0	358	79.73
1	12	2.67
2	8	1.78
3	0	0.00
4	24	5.35
5	12	2.67
6	3	0.67
7	0	0.00
8	10	2.23
9	6	1.34
10	10	2.23
11	6	1.34
Total	449	100.00

666 Table 8 summarizes the number of differences observed in each pairwise comparison. Among all comparisons, 80%  
 667 produce the identical text in reason and decision. The discrepancies come from the following two reasons: 1) Gemini  
 668 extracted different length for the same decision, e.g. in Kan et al. [25], some runs may extract “singleday lag models  
 669 underestimate the cumulative effect of pollutants on mortality 2day moving average **of current and previous day**  
 670 **concentrations** (lag=01)”, while others extract “singleday lag models underestimate the cumulative effect of pollutants  
 671 on mortality 2day moving average (lag=01)”. Similarity, for decisions, some runs yield “10 df for total mortality”, while  
 672 other runs yield “10 df”. 2) Gemini fails to extract reasons in some runs but not others, e.g. in Burnett et al. [9], the first  
 673 run generates NAs in the reasons, but the remaining four runs are identical. In Ueda et al. [50] and Castillejos et al. [11]  
 674

, runs 1 and 5 fail to extract the reasons and produce the same incomplete version, whereas runs 2, 3, and 4 produce accurate versions with reasons populated.  
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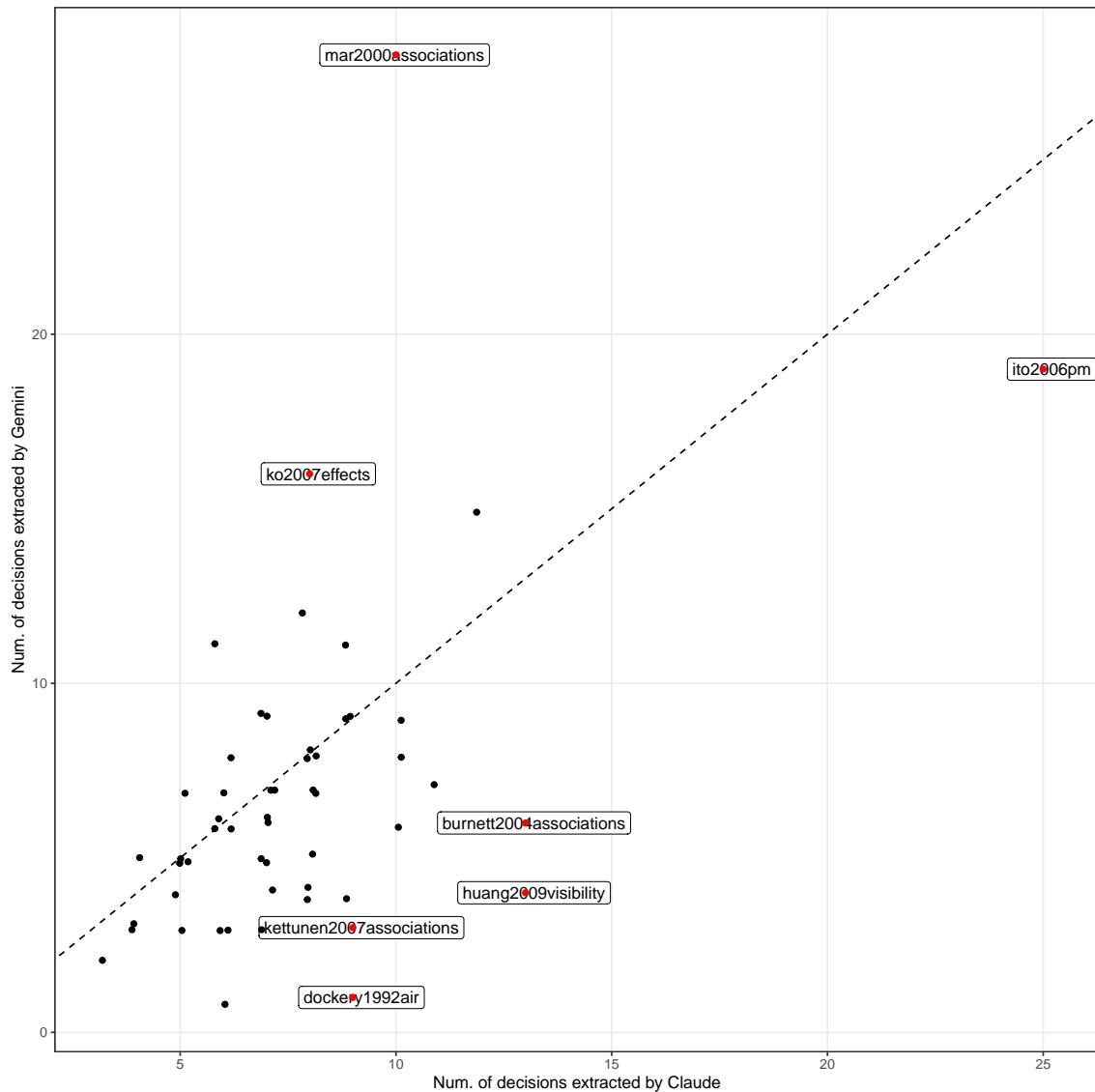
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Fig. 4. Comparison of decisions extracted by Claude and Gemini. Each point represents a paper, with the x- and y-axes showing the number of decisions extracted by Claude and Gemini, respectively. The dashed 1:1 line marks where both models extract the same number of decisions. More 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.  
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**4.4.2 LLM models.** Reading text from PDF document requires Optical Character Recognition (OCR) to convert images into machine-readable text, which currently is only supported by Anthropic Claude (claude-3-7-sonnet-latest) and Manuscript submitted to ACM  
 726  
 727  
 728



729 Google Gemini (gemini-2.0-flash). We compare the number of decisions extracted by Claude and Gemini across all  
730 62 papers in Figure 4. Each point represents a paper, with the x- and y-axes showing the number of decisions extracted  
731 by Claude and Gemini, respectively. The dashed 1:1 line marks where both models extract the same number of decisions.  
732 While both models extract decisions irrelevant to our analysis, such as sensitivity analyses and secondary analyses,  
733 Claude’s extractions tend to include more of these irrelevant decisions, examples of these include 1) the definition  
734 of “cold day” and “hot day” indicators in Dockery et al. [16] (“defined at the 5th/ 95th percentile”), 2) decisions relate  
735 to other pollutants: 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 3) the definition  
736 of black smoke and in Katsouyanni et al. [27] for secondary analysis (“restrict to days with BS concentrations below  
737 150 µg/m<sup>2</sup>”). While Gemini also capture these irrelevant decisions, such as “0-4 lag days” for air pollution exposure  
738 variables (CO, EC, K<sub>S</sub>, NO<sub>2</sub>, O<sub>3</sub>, OC, Pb, S, SO<sub>2</sub>, TC, Zn) in Mar et al. [36]. However, these cases are less frequent than  
739 Claude’s extraction and has been validated and standardized in Section 4.1.  
740

741 For both Claude and Gemini, we find they fail to link the general term “weather variables” to the specific weather  
742 variables (e.g. Dockery et al. [16] and Burnett et al. [10] for Gemini and Dockery et al. [16] and Katsouyanni et al. [27]  
743 for Claude). Although our prompt specified that some decisions may require linking information across sentences and  
744 paragraphs to identify the correct variable, this instruction doesn’t appear to be applied consistently.  
745

746 4.4.3 *Text model.* We have conducted sensitivity analysis on the text model for obtaining the decision similarity score  
747 from the Gemini outputs. The tested language models tested include 1) BERT by Google [15], 2) RoBERTa by Facebook  
748 AI [34], trained on a larger dataset (160GB v.s. BERT’s 15GB), 3) XLNet by Google Brain [55], and two domain-trained  
749 BERT models: 4) sciBERT [4], trained on scientific literature, and 5) bioBERT [30], trained on PubMed and PMC data.  
750

751 Figure 5 shows the distribution of the decision similarity and the corresponding multi-dimensional scaling visualization,  
752 where distance are calcualted from the paper similarity for each text model. At decision level, the BERT model  
753 produces the widest variation across all five models, while the similarity scores from XLNet are all close to 1. While the  
754 raw scores are not directly comparable across models due to the difference in the underlying transformer architecture,  
755 the multi-dimensional scaling (MDS) based on paper similarity scores shows a similar clustering pattern corresponding  
756 to the three main smoothing methods (LOESS, natural spline, and smoothing spline).  
757

## 758 5 Discussion

759 While the extraction of decisions from literature could be largely automated with LLMs, manual validations remains  
760 essential to ensure the quality of the extracted decisions for further analysis. The quality from the LLM ouput directly  
761 affects the amount of manual effort needed for validation and standardization. Using a default temperature of 1 and  
762 instructing the model to extract original text rather than paraphrase, we find hallucination is not a major issue with  
763 Claude and Gemini for this application. While prompt engineering is used in this work to optimize the prompt for  
764 decision extraction, an alternative is to fine-tune a local model to improve LLM performance. Such approach could  
765 be beneficial for a systematic literature review, although it would require a labelled decision dataset for training and  
766 significantly more training efforts.  
767

768 As a demonstration, we focus on the modelling decision for the baseline model in the air pollution epidemiology  
769 literature. Analyses in this fields often fit multiple models for different health outcomes. Other models, such as distributed  
770 lag models and multi-pollutant models are also commonly used to estimate relative risks and the interaction among  
771 pollutants. These factors increase the complexity of the decision extraction for LLM, as for additional models,authors  
772 often describe only the differences from the baseline model specification, assuming other decisions remain unchanged.  
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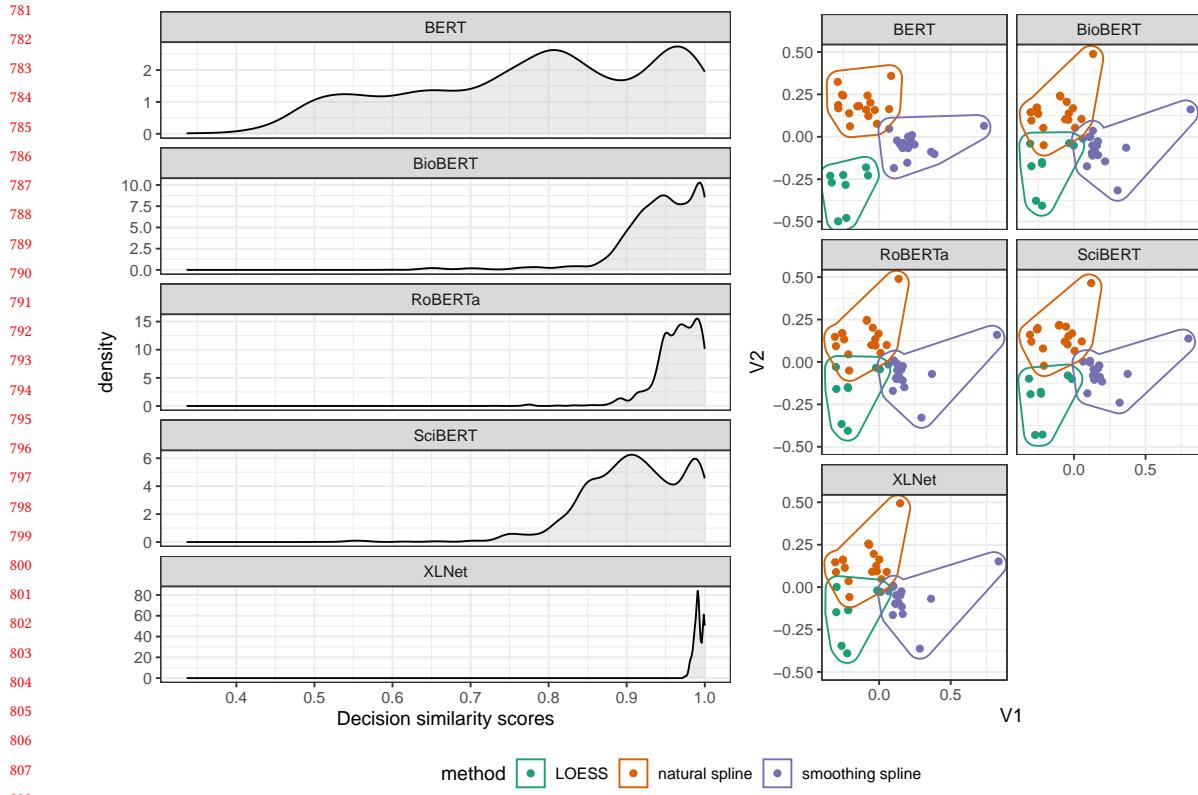


Fig. 5. Distribution of decision similarity (left) and multi-dimensional scaling (MDS) of the paper similarity scores (right) computed for five different text models (BERT, BioBERT, RoBERTa, SciBERT, and XLNet). The default language model, BERT, produces the widest variation across the five models, while the similarity scores form XLNet are all close to 1. The model BioBERT, RoBERTa, and SciBERT yield decision similar scores mostly between 0.7 to 1. All the text models shows a similar clustering structure based on the three main smoothing methods (LOESS, natural spline and smoothing spline).

The LLMs will need to be able to link the decisions across different models and identify the full set of decision for each model for cross-comparison among papers. Apart from modelling choices, other decisions in data pre-processing are also worth comparing. This would include how variables are defined and computed from the raw data.

With the advocacy for reproducibility in science, it is expected that more papers will share their code and data. Code availability can serve as a supplementary source for understanding the choices made in the analysis and cross-check against the description in the manuscript. However, decision choices could be extracted from the scripts, but the rationale behind these choices may not be easily discernible given the lack of comments in the current practice.

## 6 Conclusion

In this paper, we aim to study how analysts make decisions in their data analysis practice. While classic interviews are often conducted in small scale with toy examples, we developed a pipeline for automatically extracting decisions using LLMs (Claude and Gemini) from scientific literature. We also introduced a method for calculating paper similarity

833 through comparing the similarities among decisions and the similarity metric can be used as a distance to cluster  
 834 papers by their decision choices and visualization with dimension reduction algorithms, such as multidimensional  
 835 scaling. We applied this pipeline to a set of air pollution modelling literature that associates daily particulate matter  
 836 and daily mortality and hospital admission. From the extracted modelling decisions, we identify the most common  
 837 decision choices in this type of analysis and the paper similarity score calculation revealed the three clusters of paper  
 838 corresponding to different modelling strategies. These findings are all consistent with the general understanding of the  
 839 field, as documented in the APHENA project [28] and other methodological comparison studies [41, 49].  
 840

841 While sensitivity analyses are commonly used to assess the robustness of findings to different analytical choices, the  
 842 set of choices tested is often limited and selected subjectively by the authors. Our approach offers a new perspective by  
 843 pooling decisions made in analyses across studies in the fields. This allows for a holistic account on the alternatives in  
 844 the field and identification of both consensus and divergence within the field, providing insights for future research and  
 845 methodological development.  
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