

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

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6 Decision choices made during data analysis, along with the reasons motivating them, are central to how results are interpreted and to
7 comparisons across similar studies. However, such decisions – such as selecting the degree of freedom for a smoothing spline and the
8 rationale behind them – are rarely studied, since it is impractical to interview authors for all the alternatives and their motivations or
9 to rerun the analysis under different options. In this work, we propose a workflow to automatically extract analytic decisions from the
10 published literature and organize them into structured data using Large Language Models (Claude and Gemini). The pipeline then
11 calculates paper similarity based on the semantic similarity of these extracted decisions and their reasons, and visualizes the results
12 using clustering algorithms. We apply this workflow to a set of studies on the effect of particulate matter on mortality and hospital
13 admission, conducted by researchers worldwide, which naturally provide alternative analyses of the same question. Our approach
14 offers an efficient way to study decision-making practices and robustness in data analysis compared with traditional interviews or
15 author-focused sensitivity or multiverse analyses.

16
17 CCS Concepts: • **Applied computing** → *Document analysis*; • **Human-centered computing** → *Empirical studies in HCI*.

18
19 Additional Key Words and Phrases: Large language models

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21 **ACM Reference Format:**

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25 XXXXXXXX

26
27 **1 Introduction**

28
29 Decisions are made at every stage of data analysis: from initial data collection and pre-processing to modelling choices.
30 Different decision choices can have a direct impact to the final results, which can lead to different interpretation and
31 policy recommendations that follow. When independent analysts analyzing the same dataset even to answer the same
32 research questions, through many-analysts experiments, they often arrive at markedly different conclusions [8, 20, 43].
33 This variability in results can be attributed to the flexibility analysts have in making decisions throughout the data
34 analysis process, which Gelman and Loken [19] describe as the “garden of forking paths”. When such flexibility is
35 misused, data analysis can lead to p-hacking, selective reporting, inflated effect sizes, and other issues, undermining the
36 quality and credibility of the findings.

37
38 [this is not okay – Multiple recommendations have been proposed to improve data analysis practices, such as
39 pre-registration and multiverse analysis. Bayesian methods also offer a different paradigm to p-value driven inference
40 for interpreting statistical evidence. Most empirical studies of data analysis practices focus on specially designed and
41 simplified analysis scenarios. While informative, these setups may not adequately capture the complexity of the data
42 analysis with significant policy implications. [In practice, studying the data analysis decisions with actual applications is

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

57

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.

68 In summary, the contribution of this work includes:

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

74 2 Related work

75 2.1 Decision-making in data analysis

76 Data analysis involves making choices at every step, from initial data collection, data pre-processing to model specification,
77 and post-processing. Each decision represents a branching point where analysts choose a specific path to follow,
78 and the vast number of possible choices analysts can take forms what Gelman and Loken [19] describe as the “garden
79 of forking paths”. While researchers may hope their inferential results are robust to the specific path taken through
80 the garden, in practice, different choices can lead to substantially different conclusions. This has been empirically
81 demonstrated through “many analyst experiments”, where independent research groups analyze the same dataset to
82 address the same research questions with their own chosen analytic approach. A classic example is Silberzahn et al.
83 [43], where researchers reported an odds ratio from 0.89 to 2.93 for the effect of soccer players’ skin tone on the number
84 of red cards awarded by referees. Similar variability has been observed in structural equation modeling [41], applied
85 microeconomics [23], neuroimaging [8], and ecology and evolutionary biology [20].

86 Examples like above have rendered decision-making in data analysis as a subject to study in human computer
87 interaction. To understand how analysts making decisions during data analysis and navigating the garden of forking
88 path, researchers have conducted qualitative interviews with analysts on data analysis practices [2, 25, 30]. Visualization
89 tools have also been explored to communicate the decision process through analytic decision graphics (ADG) [31]. In
90 fairness machine learning literature, Simson et al. [44] contributed a reusable workflow that supports participatory input
91 to democratize decisions in machine learning algorithms related to fairness, privacy, interpretability and performance.
92 Conducting qualitative studies through interviews to study how assumptions and decisions are made in data analysis

practices takes a significant amount of time and effort, and the findings may not generalize to other contexts. While published research papers may not provide a complete picture of the decision-making process, they do contain valuable information about the choices made by analysts and the rationale behind them. With recent advances in Large Language Models (LLMs), it has become possible to automatically extract structured information from unstructured text. This could provide a scalable way to study decision-making practices in data analysis.

On top of qualitative studies, software tools have also developed to incorporate potential alternatives in the analysis workflow. The `DeclareDesign` package [7] introduces the MIDA framework for researchers to declare, diagnose, and redesign their analyses to produce a distribution of the statistic of interest, which has been applied in the randomized controlled trial study [6]. The `multiverse` package [32, 40] provides a framework for researchers to conduct multiverse analysis to systematically explore how different choices affect results and to report the range of plausible outcomes that arise from alternative analytic paths.

2.2 Visualization on scientific literature

With the growing volume of scientific publications and the difficulty of navigating the literature to stay informed, there is increasing interest in developing tools to visualize and recommend scientific papers. These systems link papers based on their similarity and relevance, typically determined by keywords [24], citation information (e.g. citation list, co-citation) [14], or combinations with other relevant paper metadata (e.g. author, title) [5, 15, 18, 21]. Recent approaches incorporate text-based information using topic modelling [1], argumentation-based information retrieval [45], and text embedding [37]. While metadata and high-level text-based information are useful for finding relevant papers, researchers also need tools that help them *make sense* of the literature rather than simply *locating* it. In applied data analysis, one interest is to understand how studies differ or align in their analytical approaches. Capturing the decisions and reasoning expressed in analyses on a shared theme enables the calculation of similarity metrics based on these choice and their underlying rationale, which supports clustering and visualizing paper to identify common practices in the field.

3 Methods

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

3.1 Record decisions in data analysis

Consider the following excerpt from Ostro et al. [38] that describes the modelling approach to provide evidence of an association between daily counts of mortality and ambient particulate matter (PM10):

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

To record these decisions in a tabular format, we follow the tidy data principle [48], 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. [38]:

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	degree of	parameter	3 degree of	NA
			spline	freedom		freedom	
ostro	2	relative	smoothing	degree of	parameter	3 degree of	NA
		humidity	spline	freedom		freedom	
ostro	3	temperature	NA	NA	temporal	1-day lags	NA
ostro	4	relative	NA	NA	temporal	1-day lags	NA
		humidity					

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 Character Recognition (OCR) to convert scanned images into machine-readable text – capability currently offered by Anthropic Claude and Google Gemini. In the prompt, we assign the LLM a role as an applied statistician and instruct it to generate a markdown file containing a JSON block that extract decisions from the PDF in the format described in

209 Section 3.1. We also provide a set of instructions and examples on the potential missing of reason and decision fields.
 210 Prompt engineering techniques [13, 51] are used to optimize the prompt script. The full prompt feed to the LLM is
 211 provided in the Appendix. We use the `chat_PROVIDER()` functions from the `ellmer` package [50] in R to obtain the
 212 output with Gemini and Claude API.
 213

214 215 **3.3 Validate and standardize LLM outputs**

216 The LLM outputs need to be validated and standardized before further analysis. Validation focuses on ensuring the
 217 correctness of the extracted decisions by LLMs, while standardization aims to ensure consistency in variable and model
 218 names across papers, given authors may express the same concept in different ways. For example, “mean temperature”,
 219 “average temperature”, and “temperature” all refer to the same variable, which can be all standardized to “temperature”
 220 for consistency. To help with the validation and standardization process, we developed a Shiny application that provides
 221 an interactive interface for users to review and edit the LLM outputs. A Shiny application takes a CSV of extracted
 222 decisions as input and allows three types of edits: 1) *overwrite* – modify the content of a particular cell, 2) *delete* –
 223 remove a particular irrelevant decision, and 3) *add* – manually enter a missing decision. Figure 1 illustrates the *overwrite*
 224 action for standardizing the variable NCtot (The number concentration of urban background particles <100 nm in
 225 diameter) to “pollution”: the user enters a predicate function in the filter condition box on the left panel, and the filtered
 226 data will appear interactively in the right panel. The user can then specify the variable to overwrite and the new value
 227 and the corresponding cells in the right panel will be updated. This change need to be confirmed by pressing the “Apply
 228 changes” button to update the full dataset. The corresponding `tidyverse` [49] code will then be generated in the left
 229 panel to be included in an R script, and the edited table can be downloaded for future analysis.
 230

231 232 **3.4 Calculate paper similarity and visualization**

233 Once the output has been extracted and validated, the decisions can be treated as data for further analysis. In this
 234 section, we construct a distance metric between pairs of papers based on the similarity of their decision choices. This
 235 metric can then be used as a distance matrix among papers for clustering, dimension reduction, and visualization.
 236

237 For each paper pair, a decision is considered comparable if the papers share the same variable and decision type, for
 238 example, a parameter decision on temperature or the temporal decision on humidity. For two decisions to be considered
 239 similar, both the decision choice and the rationale are taken into account. A similar choice indicates a similar final
 240 decisions are made in the analysis, whereas a similar reason reflects a shared rationale or justification for the choice,
 241 even when the choices themselves differ, potentially due to differences in the underlying data. To assign numerical
 242 value for measuring the similarity, we use the semantic similarity from text model (default to BERT). For parameter
 243 type decisions, the statistical method used also contributes to the similarity of the decision. Since semantic similarity
 244 cannot fully capture the difference betweenit statistical methods (the difference between smoothing spline and natural
 245 spline is not well represented by the textual difference of “smoothing” and “natural”), method similarity is encoded
 246 as binary: 1 if the two papers used the same method, and 0 otherwise. The paper similarity is then computed as the
 247 average similarity across all the matched methods, decisions, and reasons. The resulting paper similarity metric can be
 248 interpreted as a distance measure to cluster and visualize papers based on their decision choices.
 249

250 Because analyses vary in the decisions they report, the number of matched decisions differs across paper pairs. In
 251 practice, some studies may not fully report the decision and reason for every choice made, leading to missing data for
 252 the matched decisions. Although paper similarity can be calculated based on all available matched decisions, care
 253 should be taken for pairs with only a small number of matches, as the paper similarity may be overly influenced by one
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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 or two decisions. To address this, users may focus on a set of decisions shared across papers and on papers that report a
 314 minimal number of these decisions when calculating paper similarity.
 315

316 4 Results

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

326 From the 56 studies examining the effect of particulate matters (PM_{10} and $PM_{2.5}$) on mortality and hospital admission,
 327 we focus on the baseline model reported in each paper, excluding secondary models (e.g. lag-distributed models) and
 328 sensitivity analysis. We also exclude decisions on other pollutants, such as nitrogen dioxide (NO_2). This yields 242
 329 decisions extracted using Gemini, averaging approximately 4 decisions per paper.
 330

331 4.1 Validation and standardization of LLM outputs

332 Table 2. Summary of validation and standardization edits made during the review process.
 333

334 Reason	335 Count
336 Remove decisions out of scope: other pollutants and sensitivity analysis	50
337 Edit made to recode smoothing parameter unit to per year	45
338 Duplicates	9
339 Fix incorrect capture	9
340 Edit made due to decisions are too general, e.g. minimum of 1 df per year was required	6
341 Remove decisions related to definition of variables, e.g. season	5
342 Total	124

343 Table 2 summarizes the number of edits made during the review process using the Shiny application. These edits
 344 fall into two main categories: 1) correcting LLM outputs and 2) standardizing extracted decision. The first category
 345 includes fixing incorrect captures, removing non-decision (e.g. definition of variables), removing duplication, excluding
 346 irrelevant decisions (e.g. sensitivity analyses), and excluding decisions whose stated reasons reflect general guidelines
 347 rather than actual choices (e.g. “minimum of 1 degree of freedom per year is required”).
 348

349 Standardization addresses variation in how authors express variable names and decisions. For example, variable
 350 names such as “mean temperature” and “average temperature” refer to the same variable and should be aligned for
 351 comparison for later decision similarity calculation. Variable names are manually standardized into four main categories:
 352

- 353 • **temperature:** “mean temperature”, “average temperature”, “temperature”, “air temperature”, “ambient tempera-
 354 ture”
- 355 • **humidity:** “dewpoint temperature” and its hyphenated variants, relative humidity”, “humidity”

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%)

- **PM:** “pollutant”, “pollution”, “particulate matter”, “particulate”, “PM10”, “PM2.5”
- **time:** “date”, “time”, “trends”, “trend”

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

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

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

387 This variability makes manual standardization impractical, hence we apply a secondary LLM process (claude-3-
 388 7-sonnet-latest) using the ellmer package to convert temporal decisions into a consistent format: **multi-day**: lag
 389 [start]-[end] and **single-day**: lag [start], . . . , lag [end]. For instance, “6-day average” is converted to
 390 “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”.

395 4.2 Exploratory analysis of decision choices

396 Table 3 summarizes the missingness of the decisions and reason. While most papers report their decision choices
 397 (e.g. use of five degree of freedom), 55% of decisions lack a stated rationale for the choice. Table 4 lists the eight most
 398 frequently reported decision: parameter and temporal choice for time, PM, temperature, and humidity.

- **TODO** something about result validation of LLM output: We also observe data quality with the extraction:
 401 for example in Lee et al. [29], the variable recorded is “smoothing parameter”. Authors are unclear about the
 402 delivery Specify how much of validation and review has been done.

403 Table 4. Count of variable-type decisions in the Gemini-extracted decisions. The most commonly reported decision are the parameter
 404 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

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
temperature	temporal	23
humidity	temporal	19
PM	parameter	9
time	temporal	3

427
 428 Table 5 reports the parameter-related decisions captured in the literature. They refer to the number of knots or degree
 429 of freedom for spline methods (natural and smoothing spline) applied to variable time, humidity and temperature. For
 430 consistency, all values have been converted to a *per year* scale. The selection of knot for natural spline has less variation
 431 than the degree of freedom choices for smoothing spline. Choices for temperature and humidity tend to be close, given
 432 they are both weather related variables, while the choices for time are more varied inherently. This tabulation offers a
 433 reference set for potential options for future studies and help to identify anomalies and special treatment in practice.
 434 Notable example includes the use of 7.7 degree of freedom in Castillejos et al. [12], and highly flexible choices of 30 and
 435 100 in Moolgavkar [35] and Moolgavkar [36], respectively. While most papers choice to report the smoothing parameter
 436 as a constant value, Schwartz [42] specifies it as a proportion of the data (“5% of the data” and “5% of the data”).
 437

438 Table ?? summarizes the temporal lag choices for PM, temperature, and humidity. Both single and multiple day lags
 439 are generally considered up to five days prior (lag 5). [TODO: check multi-day starts from one].
 440

441 Table 5. Options captured for parameter choices for time, humidity, and temperature variables in the Gemini-extracted decisions.
 442 The choices for natural spline knots are generally less varied than the degree of freedom choices for smoothing spline. Choices for
 443 temperature and humidity tend to be close, given they are both weather related variables, while the choices for time are more varied
 444 inherently.
 445

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, NA
smoothing spline	humidity	2, 3, 4, 6, 8, 50
smoothing spline	temperature	2, 3, 4, 6, 8, 50
smoothing spline	time	1, 3, 4, 5, 6, 7, 7.7, 8, 9, 10, 12, 30, 100, NA

460 4.3 Paper similarity and clustering

461 For computing the decision similarity score, we include the first 6 most common variable-type decisions as suggested
 462 in Table 4. Figure 3 shows the clustering of the 48 papers based on the decision similarity scores. The dendrogram is
 463 generated using hierarchical clustering, and the labels are colored according to the most common smoothing method
 464 used in each paper. The clustering reveals three distinct groups of papers, which reflect the modelling strategies differ
 465 in the European (LOESS) and U.S. (...) studies [more on the APHENA].
 466

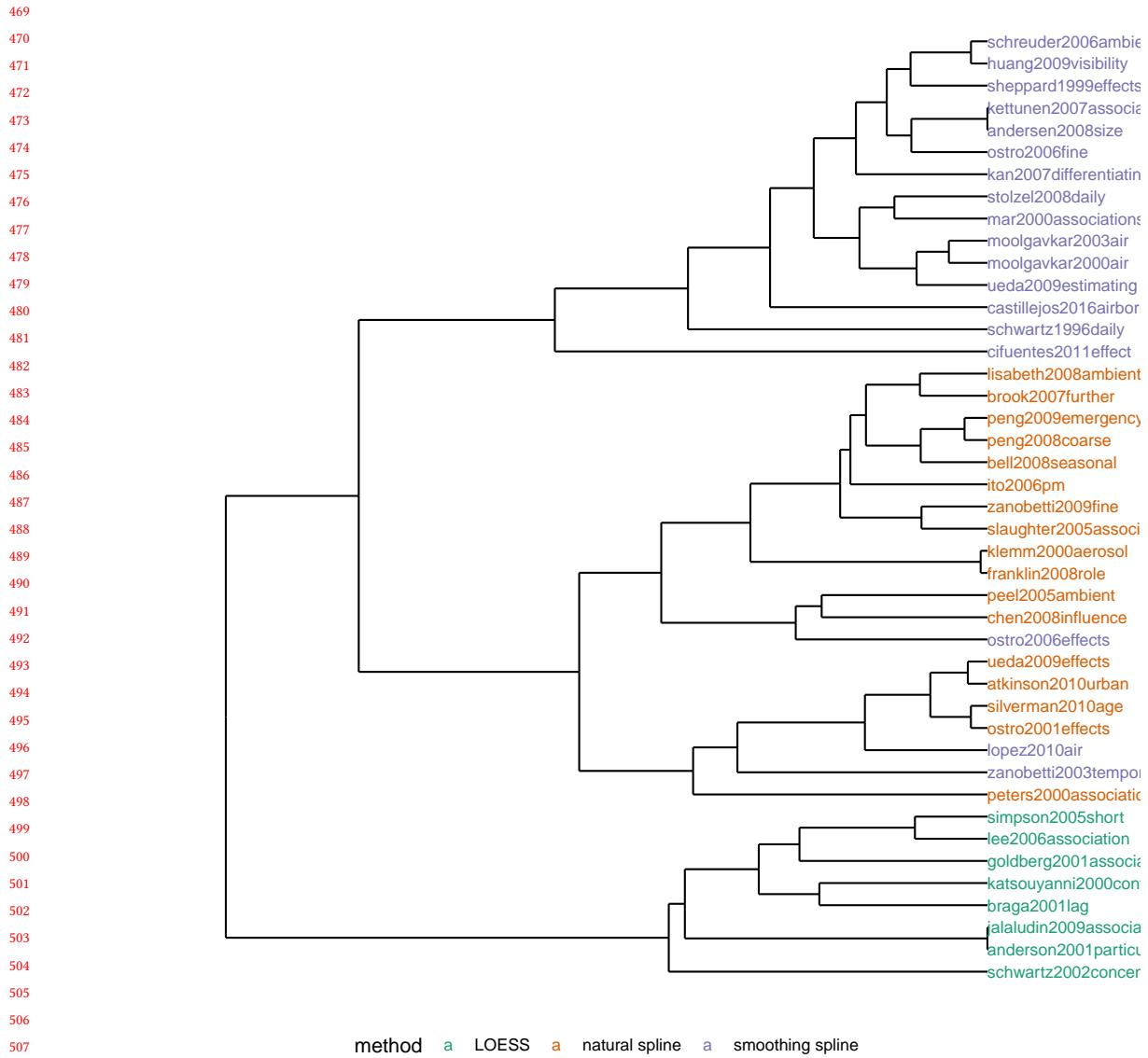


Fig. 2. The dendrogram (left) and multi-dimensional scaling (MDS) (right) based on paper similarity distance for 62 air pollution mortality modelling literature. The papers are colored by the most common smoothing method used. The MDS reveals the three distinct groups of papers. This grouping corresponds to the modelling strategies differ in the European and U.S. studies, documented in ALPHENA.

5 Discussion

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

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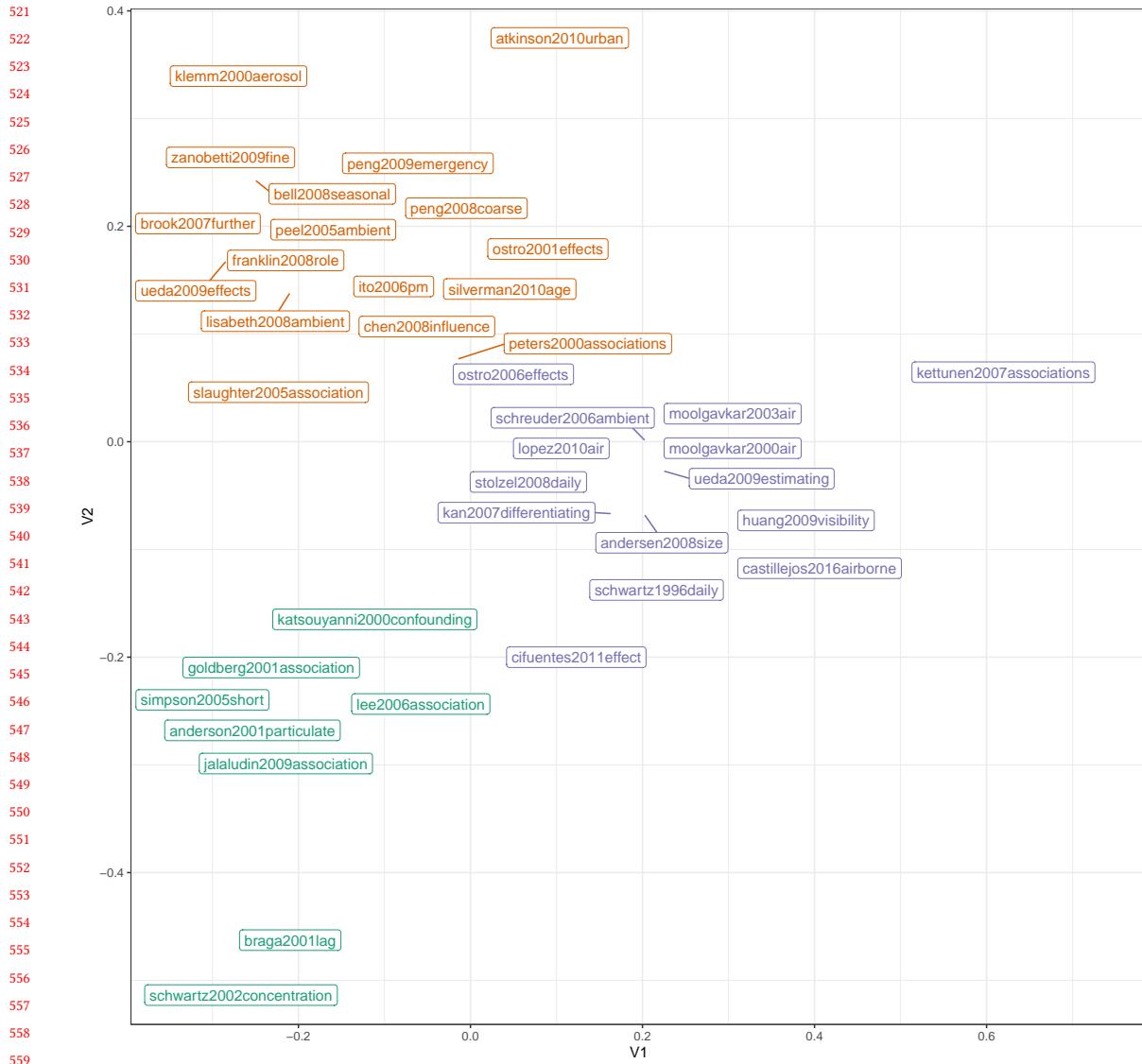


Fig. 3. The dendrogram (left) and multi-dimensional scaling (MDS) (right) based on paper similarity distance for 62 air pollution mortality modelling literature. The papers are colored by the most common smoothing method used. The MDS reveals the three distinct groups of papers. This grouping corresponds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

In this section, we examine the reproducibility for using LLMs for text extraction tasks in Section 5.1, discrepancies between different LLM models: Gemini (gemini-2.0-flash) and Claude (claude-3-7-sonnet-latest) in Section 5.2, and the sensitivity of our paper similarity calculation pipeline to the choice of text model used for computing decision similarity scores in Section 5.3.

573 5.1 LLM reproducibility

574
 575 For our text extraction task, we test the reproducibility of Gemini (`gemini-2.0-flash`) by repeating the text extraction
 576 task 5 times for each of the 56 papers. For each of the 31 papers, five runs yield $5 \times 4/2 = 10$ pairwise comparisons per
 577 field and including both the “reason” and “decision” fields results in a total of $31 \times 10 \times 2 = 620$ pairs. We exclude the
 578 pairs that have different number of decisions since it would require manually align the decision to compare and this left
 579 us with 449 out of 620 (72%) pairwise comparisons. Table 6 shows an example of such comparison in Andersen et al. [3],
 580 where all the four reasons are identical among the two runs, hence a zero number of difference.
 581

582
 583 Table 6. An example of comparing the text extraction in decisions in Andersen 2008.
 584

585 Variable	Run1	Run2
587 NCtot	6day average (lag 05)	6day average (lag 05)
588 calendar time	3 4 or 5 df/year	3 4 or 5 df/year
589 dew-point temperature	4 or 5 df	4 or 5 df
590 temperature	4 or 5 df	4 or 5 df

593 Table 7 summarizes the number of differences observed in each pairwise comparison. Among all comparisons, 80%
 594 produce the identical text in reason and decision. The discrepancies come from the following reasons:
 595

- 596 • Gemini extracted different length for the same decision, e.g. in Kan et al. [26], some runs may extract “singleday
 597 lag models underestimate the cumulative effect of pollutants on mortality 2day moving average **of current**
 598 **and previous day concentrations** (lag=01), while others extract “singleday lag models underestimate the
 599 cumulative effect of pollutants on mortality 2day moving average (lag=01)”. Similarity, for decisions, some runs
 600 may yield “10 df for total mortality”, while other runs yield “10 df”. Similar extraction appears in Breitner et al.
 601 [9].
- 602 • Gemini fails to extract reasons in some runs but not others, e.g. in Burnett et al. [10], the first run generates
 603 NAs in the reasons, but the remaining four runs are identical. In Ueda et al. [47] and Castillejos et al. [12], runs
 604 1 and 5 fail to extract the reasons and produce the same incomplete version, whereas runs 2, 3, and 4 produce
 605 accurate versions with reasons populated.

606 Table 7. Number of differences in the reason and decision fields across Gemini runs for papers with consistent number of decisions
 607 across runs.
 608

611	612 Num. of difference	613 Count	614 Proportion (%)
615	0	358	79.73
616	1	12	2.67
617	2	8	1.78
618	3	0	0.00
619	4	24	5.35
620	5	12	2.67
621	6	3	0.67
622	7	0	0.00

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

628	Num. of difference	629 Count	630 Proportion (%)
630	8	631 10	632 2.23
631	9	632 6	633 1.34
632	10	633 10	634 2.23
633	11	634 6	635 1.34
634	Total	635 449	636 100.00

637 5.2 LLM models

638 Reading text from PDF document requires Optical Character Recognition (OCR) to convert images into machine-
 639 readable text, which currently is only supported by Anthropic Claude (claude-3-7-sonnet-latest) and Google Gemini
 640 (gemini-2.0-flash).

641 We compare the number of decisions extracted by Claude and Gemini across all 56 papers in ?@fig-claude-gemini.
 642 Each point represents a paper, with the x- and y-axes showing the number of decisions extracted by Claude and Gemini,
 643 respectively. The dashed 1:1 line marks where both models extract the same number of decisions. Most points fall below
 644 this line, indicating that Claude extracts more decisions – often from data pre-processing or secondary data analysis
 645 steps requiring more manual validation – whereas Gemini focuses more on modelling choices relevant to our analysis.
 646 Some of these decisions captured by Claude are

- 647 • the definition of “cold day” and “hot day” indicators in Dockery et al. [17] (“defined at the 5th/ 95th percentile”),
- 648 • the choice to summarize NO₂, O₃, and SO₂ using a “24 hr average on variable” in Huang et al. [22], and
- 649 • the definition of black smoke and in Katsouyanni et al. [27] for secondary analysis (“restrict to days with BS
 650 concentrations below 150 µg/m²”).

651 Gemini sometimes also include irrelevant decisions, such as in Mar et al. [34], where secondary analysis choices like
 652 “0-4 lag days” for air pollution exposure variables (CO, EC, K_S, NO₂, O₃, OC, Pb, S, SO₂, TC, Zn) are captured. However,
 653 these cases are less frequent, resulting in outputs with less noise overall.

654 For both Claude and Gemini, we find they fail to link the general term “weather variables” to the specific weather
 655 variables. For example Gemini misses this link in Dockery et al. [17] and Burnett et al. [11], while Claude does so in
 656 Dockery et al. [17] and Katsouyanni et al. [27]. Although our prompt specified that some decisions may require linking
 657 information across sentences and paragraphs to identify the correct variable, this instruction doesn’t appear to be
 658 applied consistently.

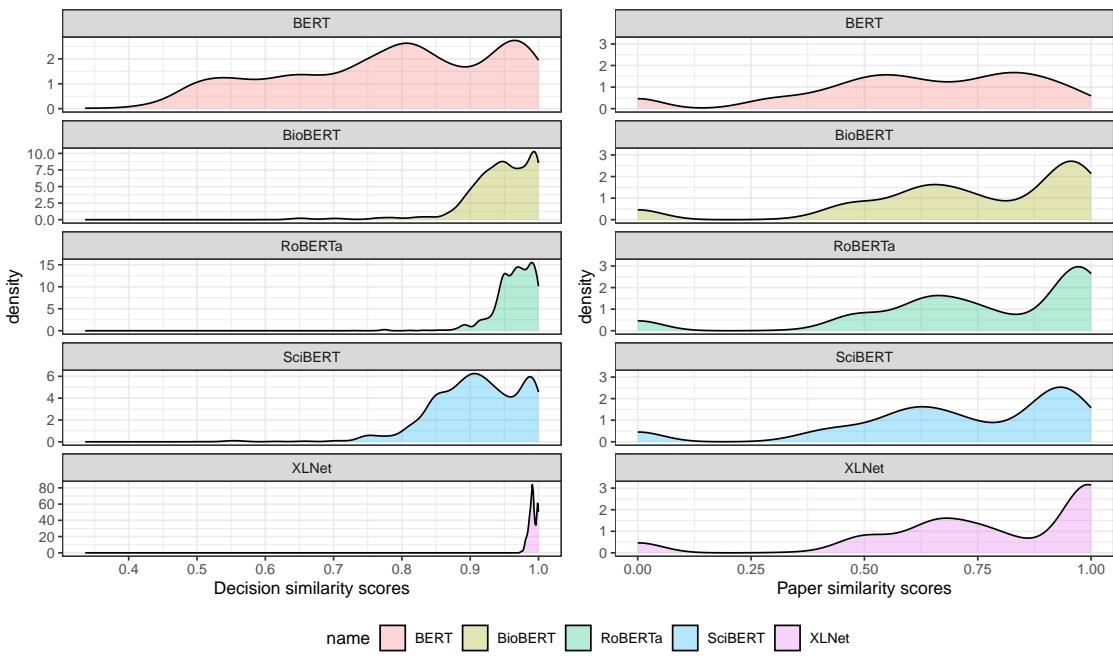
659 5.3 Text model

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

- 662 1) BERT by Google [16],
- 663 2) RoBERTa by Facebook AI [33], trained on a larger dataset (160GB v.s. BERT’s 15GB),
- 664 3) XLNet by Google Brain [52], and
- 665 two domain-trained BERT models:

- 677 4) sciBERT [4], trained on scientific literature, and
 678 5) bioBERT [28], trained on PubMed and PMC data.
 679

680 Figure 4 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 5 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



712 Fig. 4. Distribution of decision similarity (left) and paper similarity (right) scores for five different text models (BERT, BioBERT,
 713 RoBERTa, SciBERT, and XLNet). The default language model, BERT, produces the widest variation across the five models, while
 714 the similarity scores form XLNet are all close to 1. The model BioBERT, RoBERTa, and SciBERT yield decision similar scores mostly
 715 between 0.7 to 1.
 716

717 5.4 Others

721 There are other decisions in an analysis that are worth comparing and documenting. For example data pre-processing
 722 decisions, e.g. how pollutant series are defined and collected, treatment on missing values, etc. Again, for a complete
 723 review of the field, these decisions ideally would be included, but for our demonstration of idea, we focus on the modelling
 724 decisions. Spatial decisions are generally not well captured because it often conducted uniformly as estimating the city
 725 individually to accommodate city heterogeneity. Some papers only consider a handful of cities, while in larger studies
 726 the individual city effects are then pooled together using random effect.
 727

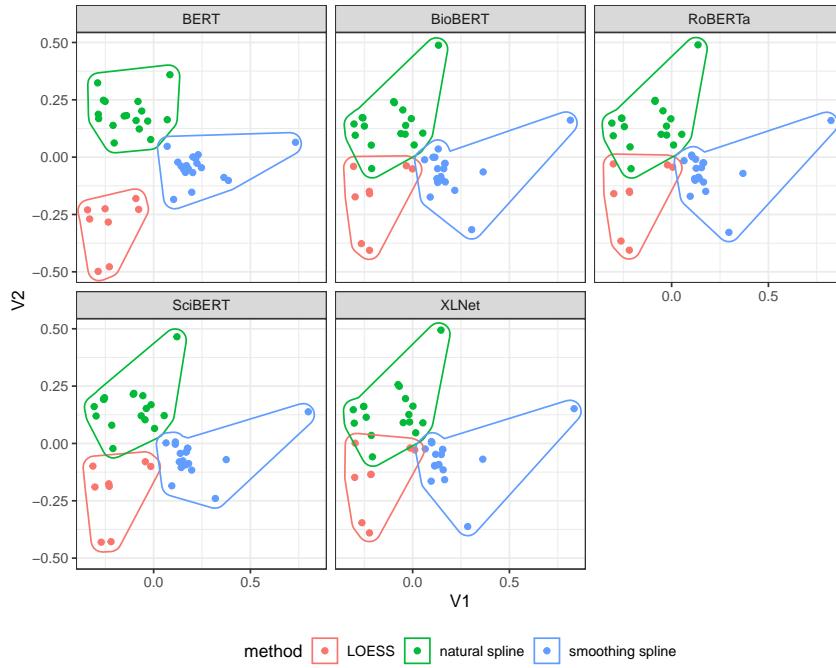


Fig. 5. The multi-dimensional scaling (MDS) of the paper similarity scores from each text model: all showing a similar clustering pattern of the three main smoothing methods. The points are colored by the most common method used in the paper, and the hulls are drawn around each method group.

The variation in the choice of parameters degree of freedom or knot for smoothing can motivate separate investigation on the sensitivity analysis. For instance, parameters that exhibit a wide range of choices across studies may indicate areas of uncertainty or debate within the field, suggesting that further investigation is needed to assess their impact on study outcomes [39, 46].

With LLMs, the extraction of decisions from literature could be largely automated, but manual review is still needed to ensure the quality of the extracted decisions. We also find secondary LLMs can be used to standardize the extracted decisions, such as for temporal lag choices from text expressing this decision in various ways. In this work, we use prompt engineering to optimize the prompt for extracting decisions from general LLMs (Claude and Gemini). Fine-tuning a local model is an alternative approach for a locally-trained model. While it could potentially yield more accurate extraction and hence less manual review, for a systematic literature review, it would require substantially more training efforts and a labelled decision dataset. We also find sometimes the prompt is not fully followed throughout the extraction (example). Claude and Gemini...

Currently, only one model per paper - some have comparison of GLM and GAM, compare different pollutants, stratify by

With the advocacy for reproducibility in science, it is expected that more papers will share their code and data. The availability of the code could be a supplementary source for understanding the decisions made in the analysis and cross comparison of the manuscript with the code. However, given the lack of comments in the current practice, we are not there to extract reasons for the decisions encoded in the script.

781 6 Conclusion

782 In this paper, [we study how decisions are made in practical data analysis]. We developed a pipeline for automatically
 783 extracting decisions using LLMs (Claude and Gemini) and introduced a method for calculating paper similarity through
 784 decision similarity. This similarity metric enables us to cluster papers by their decision choices and visualization through
 785 hierarchical clustering and multidimensional scaling. We applied this pipeline to mortality/ hospital admission – PM
 786 modelling literature and extracted key modelling decisions, such as the choice of smoothing methods and parameters
 787 for time, temperature, and humidity, and revealed paper clusters that correspond to different modelling strategies, as
 788 documented in the APHENA project.

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

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