An LLM-based pipeline for understanding decision choices in data analysis from published literature

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Decision choices, such as those made when building regression models, and their rationale are essential for interpreting results and understanding uncertainty in an analysis. However, these decisions are rarely studied because tracing every alternatives considered by authors is often impractical, and reworking a completed analysis is generally of limited interest. Consequently, researchers must manually review large bodies of published analyses to identify common choices and understand how choices are made. In this work, we propose a workflow to automatically extract analytic decisions and their reasons from published literature using Large Language Models. Our method also introduces a paper similarity measure based on decision similarity and visualization methods using clustering algorithms. As an example, this workflow is applied to analyses studying the effect of particulate matter on mortality. This approach enables scalable and automated studies of decision choices in applied data analysis, providing an alternative to existing qualitative and interview-based studies.

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

Additional Key Words and Phrases: Large language models

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1 Introduction

TODO: need references

Decisions are made at every stage of data analysis, from initial data collection and preprocessing to modeling. One might expect well-trained researchers to make similar choices when faced with the same analytical task, yet evidence suggests otherwise. Many-analyst experiments show that independent analysts often arrive at markedly different conclusions, even when analyzing the same dataset to answer the same research question [9, 22, 69]. This variation in analytical decision-making, described by Gelman and Loken [21] as the "garden of forking paths," can undermine the quality and credibility of reported results and hinder comparability across studies. For junior researchers who lack guidance, this variability may lead to over reliance on default statistical software settings or arbitrary choices made without clear justification.

A common approach to investigate uncertainty in decision choices is sensitivity analysis, where researchers systematically vary key decisions in their analysis to assess the robustness of their findings. Multiverse analysis extends this idea by evaluating *all* plausible combinations of analytical choices to examine how results vary across the full decision space [8, 64]. However, what an analyst consider "reasonable" is subjective and may not reflect the full range of options commonly used in practice. Even when a reasonable set of alternatives is tested, the sensitivity analysis may be of

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limited interest to other researchers facing a similar problem, who are seeking evidence to inform comparable decision choices and their rationale. Ideally, decision-making in applied research would be studied by following experienced analysts throughout the entire analysis process to capture their reasoning. In reality, this is rarely feasible and not scalable.

While individual studies may not capture the full range of reasonable decision options, crowdsourcing decisions from a collection of studies on a shared theme creates a "many-analyst" setting that reveals how analysts make choices and justify them in practice. Classic research training typically involves reading through the literature to understand how decisions are made and to learn the common choices. This process now has the possibility to be automated at scale given recent LLMs' ability to follow instructions to extract structured information from unstructured text. In this work, we propose a new approach for studying data analysis decision choices by automatically extracting decisions from scientific literature using Large Language Models (LLMs). We develop a tabular schema to record decisions, automate the extraction process with LLMs, and introduce a new paper similarity measure based on decision similarity, which serves as a distance metric for dimension reduction methods to visualize papers group according to their decision patterns.

We apply this workflow to a set of 56 air pollution modelling studies estimating the effect of particulate matter (PM2.5 or PM10) on mortality and hospital admissions. This type of studies is typically analyzed using Poisson generalized linear models (GLMs) or generalized additive models (GAMs). Analysis of the extracted decisions reveals common choices for decisions considered in this type of studies such as the number of knots or degree of freedom for smoothing methods and the temporal lags for time and weather variables. Multi-dimensional scaling on the paper similarity distance finds three distinct clusters corresponding to different smoothing methods – LOESS, natural spline, and smoothing spline – used in European and U.S. studies. These findings align with the APHENA project [42], which synthesizes research from multiple studies in Europe and North America by expert investigators.

In this workflow, we also provide detailed documentation on the validation and standardization of LLM outputs. Because LLMs generate results probabilistically, it is not yet clear how these outputs should be validated for downstream analysis in practice. We outline the validation and standardization process, including the use of a developed Shiny application in R for reviewing decisions, the types of edits made through validation, and secondary standardization of decisions. Additionally, we conduct sensitivity across different LLM providers and assess the reproducibility of the text extraction from single LLM models. We aim to offer guidance for future studies seeking to extract structured information from unstructured text using LLMs.

In summary, the contribution of this work includes:

- A scalable and automated approach to study data analysis decision choices through extracting of decisions from published scientific literature using LLMs,
- A new method to construct paper similarities based on the decision and the semantic similarity of their rationale,
- A data schema for summarizing decisions made in applied studies in a tidy format,
- A shiny GUI tool for validating LLM outputs for editing tables, and
- A dataset of decisions and rationale, along with metadata, compiled from 62 studies in air pollution mortality modelling.

2 Related work

2.1 Analytic decision making in data analysis

Data analysis is a complex and iterative process [33–35] that involves multiple stages, including data collection, cleaning, visualization, modeling, and communication. At each stage, analysts make decisions informed by domain practices, statistical knowledge, and feedback from the data. These decisions, such as which variables to include in a model, how to handle missing data, and which statistical methods to use, act as branching points in the analysis workflow. The full set of possible paths through these branching points form what Gelman and Loken [21] describe as the "garden of forking paths". While one might expect well-trained researchers will often converge to similar decision choices, empirical evidence suggests otherwise. "Many analyst experiments" show that independent research groups analyze the same dataset to address the same research questions can arrive at widely different conclusions. For example Silberzahn et al. [69] asks 29 groups of analysts to conduct an analysis to address the same research questions *whether soccer players with dark skin tone are more likely than those with light skin tone to receive red cards from referees*. Researchers reported an estimated effect size from 0.89 to 2.93 in odds ratio, 70% of the teams found a statistically significant positive effect while others don't, and 21 unique combinations of covariates are used by 29 different analyses. Similar experiements has been observed in structural equation modeling [65], applied microeconomics [31], neuroimaging [9], and ecology and evolutionary biology [22].

Examples like the above illustrate how analytical decisions introduce uncertainty into data analysis. These uncertainties have been widely discussed for policy recommendation [42] and their applications in health, finance, and other domains. To help researchers avoid misusing their "researcher degree of freedom", guidelines and checklists have been developed, informed by demonstrations of how such misuse can lead to p-hacking and inflated effect size [70, 75]. Pre-registration is a common practice in medicine and biostatistics, yet Pang et al. [60] found that this is not well-adopted among HCI researchers. Given the nuanced nature of data analysis, more work have examined how analysts make decisions in practice, through interviews in both academia and industry. These studies include qualitative analysis of analytical decisions [36], interviews with data analysts about exploratory data analysis practice in industry [2, 39], interviews with data workers on how they consider alternatives in data analysis [48], and interviews researchers about their analysis decisions in published studies [49]. Participatory studies, like in the many analyst experiments, are also used to support participatory input to democratize decisions in fairness machine learning [71].

In addition to qualitative studies, software tools have developed to help researchers account for alternatives and uncertainties in the analysis workflow and make informed analytical decisions. Examples include `Tea` [33], which support general statistical analysis; `Tisane` [35], which guides choices in generalized linear mixed-effects models (GLMMs); and `MetaExplore` [37], which allows for meta-analysis to account for decision uncertainty (epistemic uncertainty) during the studies. The `DeclareDesign` package [8] in R 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 [7]. Multiverse analysis 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. Downstream works expand on how to author and visualize multiverse analysis [50], create R software for multiverse analysis using tidyverse syntax [26, 64], and debugging tools [24].

2.2 Automatic information extraction with LLMs

In natural language processing, information extraction is a task focus on extracting structured information from unstructured text. A common sub-task is named entity recognition (NER), like identifying person names, locations, and organizations in text [57]. Earlier approaches relied on rule-based systems and regular expressions to extract information. More recent advances, including conditional random fields [45], word embeddings such as word2vec [54], and transformer-based architectures like BERT [17], have led to modern information extraction methods that use large language models with prompting. [TODO: something about prompt engineering]

Using LLMs to extract unstructured text offers the advantage of automating the process at scale. Applications have been seen in epidemiology data [27], scientific literature [43], clinical data [20, 23, 29, 68], chemistry knowledge [66], and polymer science [25], climate extreme impact [47], phenotypes [4], and material properties [62]. Unlike classic NER tasks, such as extracting clinical data, which typically involves short spans of 1-4 tokens, extracting decision choices and their rationales from published literature often requires handling longer spans. These decisions are inherently less structured and more context-dependent than standard entities, making LLM-based extraction relevant and suitable.

2.3 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 [32], citation information (e.g. citation list, co-citation) [15], or combinations with other relevant paper metadata (e.g. author, title) [6, 16, 19, 28]. Recent approaches incorporate text-based information using topic modelling [1], argumentation-based information retrieval [72], and text embedding [58]. 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

In this section, we present the workflow for extracting decisions from published literature using Large Language Models (LLMs). We first describe the data structure for recording decisions, followed by the four main steps: 1) automatic extraction from literature with LLMs, 2) validation and standardization of LLM outputs, 3) calculation of paper similarity, and 4) visualization paper similarity using clustering or dimension reduction methods. The section concludes with an illustration summarizing the workflow.

3.1 Record decisions in data analysis

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

Consider the following excerpt from Ostro et al. [59] 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 [76], 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. [59]:

> 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. [41]:

> 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 Antropic 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 Section 3.1. We also provide a set of instructions and examples on the potential missing of reason and decision fields. Prompt engineering techniques [14, 79] are used to optimize the prompt script. The full prompt feed to the LLM is provided in the Appendix. We use the `chat_PROVIDER()` functions from the `ellmer` package [78] in R to obtain the output with Gemini and Claude API.

3.3 Validate and standardize LLM outputs

The LLM outputs need to be validated and standardized before further analysis. Validation focuses on ensuring the correctness of the extracted decisions by LLMs, while standardization aims to ensure consistency in variable and model names across papers, given authors may express the same concept in different ways. For example, "mean temperature", "average temperature", and "temperature" all refer to the same variable, which can be all standardized to "temperature" for consistency. To help with the validation and standardization process, we developed a Shiny application that provides an interactive interface for users to review and edit the LLM outputs. A Shiny application takes a CSV of extracted decisions as input and allows three types of edits: 1) *overwrite* – modify the content of a particular cell, 2) *delete* – remove a particular irrelevant decision, and 3) *add* – manually enter a missing decision. Figure 1 illustrates the *overwrite* action for standardizing the variable NCtot (The number concentration of urban background particles <100 nm in diameter) to "pollution": the user enters a predicate function in the filter condition box on the left panel, and the filtered data will appear interactively in the right panel. The user can then specify the variable to overwrite and the new value and the corresponding cells in the right panel will be updated. This change need to be confirmed by pressing the "Apply changes" button to update the full dataset. The corresponding `tidyverse` [77] code will then be generated in the left panel to be included in an R script, and the edited table can be downloaded for future analysis.

3.4 Calculate paper similarity and visualization

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

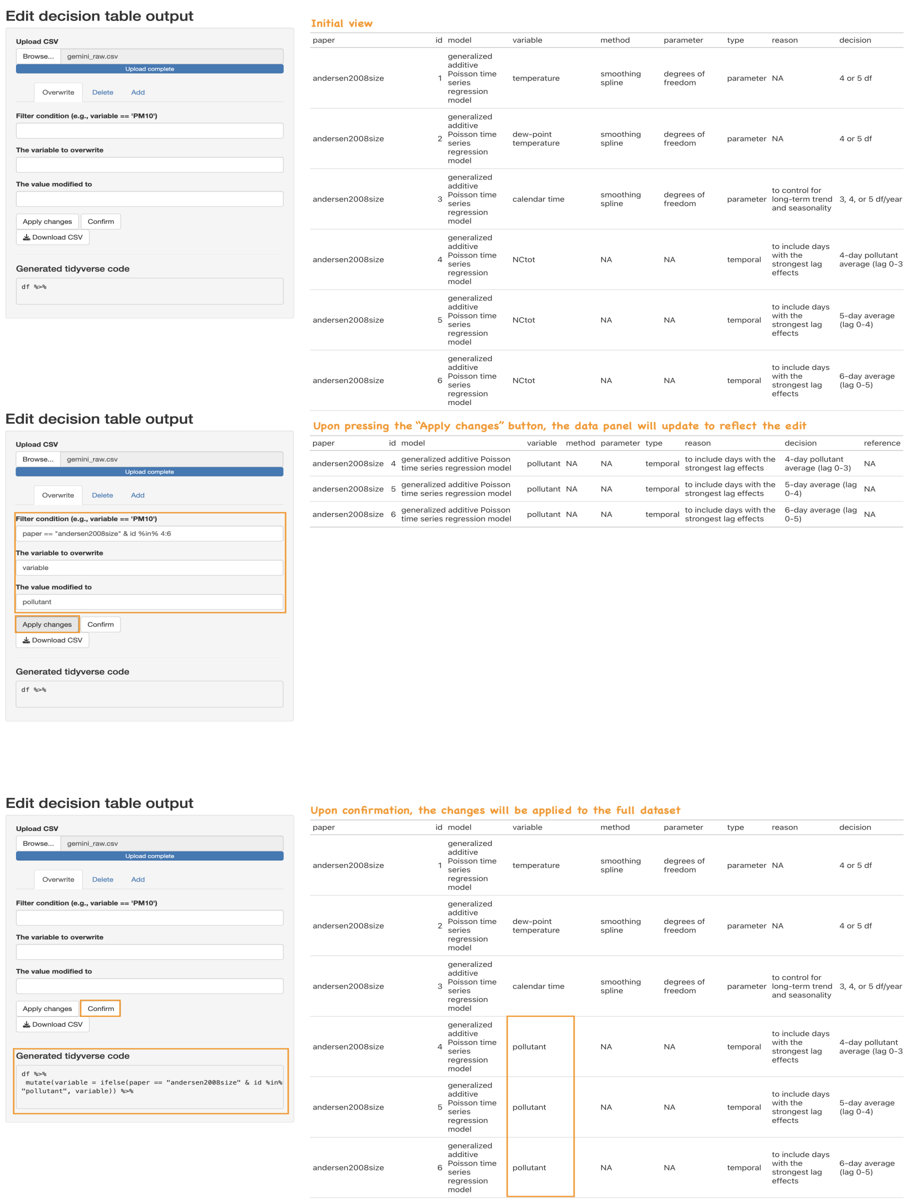

Fig. 1. The Shiny application interface to validate and standardize Large Language Model (LLM)-generated output. (1) the default interface after loading the input CSV file. (2) The table view will update interactively to reflect the edit: for paper with handle “andersen2008size” and id in 4, 5, 6, replace 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.

For each paper pair, a decision is considered comparable if the papers share the same variable and decision type, for example, a parameter decision on temperature or the temporal decision on humidity. For two decisions to be considered similar, both the decision choice and the rationale are taken into account. A similar choice indicates a similar final decisions are made in the analysis, whereas a similar reason reflects a shared rationale or justification for the choice, even when the choices themselves differ, potentially due to differences in the underlying data. To assign numerical value for measuring the similarity, we use the semantic similarity from text model, using the `text` package [44]. We first obtain the text embedding for all the reason and decisions and calculate the cosine similarity between the matched reason and decisions. For parameter type decisions, the statistical method used also contributes to the similarity of the decision. Since semantic similarity cannot fully capture the difference betweenit statistical methods (the difference between smoothing spline and natural spline is not well represented by the textual difference of "smoothing" and "natural"), method similarity is encoded as binary: 1 if the two papers used the same method, and 0 otherwise. The paper similarity is then computed as the average similarity across all the matched methods, decisions, and reasons. The resulting paper similarity metric can be interpreted as a distance measure to cluster and visualize papers based on their decision choices.

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

3.5 Summary

Figure 2 summarises the entire workflow for extracting decisions from published literature using Large Language Models (LLMs) and analyzing the extracted decisions. Once researchers have identified a set of literature of interest and a prompt to instruct LLMs to extract decisions from the literature. The outputs from LLM need to be validated and standardized before further analysis due to authors' varied writing styles. The validated data can then be used to conduct exploratory analysis of decision choices and one task is to calculate paper similarity based on the decision similarity. This paper similarity measure can be seen as a distance metric among papers, which can be used for clustering and dimension reduction for visualizing papers.

4 Results

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

4.1 Validation and standardization of LLM outputs

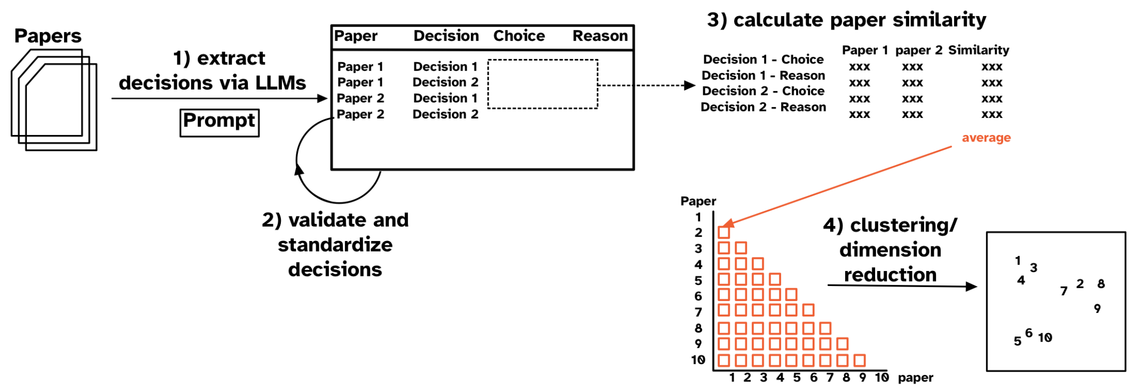

Fig. 2. The workflow for extracting decisions from published literature using Large Language Models (LLMs) and analyzing the extracted decisions. The workflow consists of four main steps: (1) Extract decisions automatically from literature with LLMs, (2) Validate and standardize LLM outputs, (3) Calculate paper similarity and visualization, and (4) visualization with clustering or dimension reduction methods.

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

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

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

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

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

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

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

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

Decisions themselves also require standardization. For example, the smoothing parameter (number of knots and degree of freedom) may be expressed *per year* or *in total*, and temporal lag decision may be expressed in different formats (e.g. "6-day average", "mean of lags 0+1", "lagged exposure up to 6 days"). Smoothing parameter units are manually recoded to a *per year* basis for consistency, asreflected in Table 2. Temporal decision show a wider variety, 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, mean 0+1+2" and
- **single-day lags**, such as "lagged exposure up to 6 days", "lag days from 0 to 5".

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

4.2 Exploratory analysis of decision choices

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

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

Variable	Type	Count
time	parameter	44
PM	temporal	39
temperature	parameter	35
humidity	parameter	25

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

Variable	Type	Count
temperature	temporal	23
humidity	temporal	19
PM	parameter	9
time	temporal	3

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

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

Table 5 presents the parameter-related decisions extracted for spline methods (natural and smoothing spline) applied to variable time, humidity and temperature. These decisions concern the number of knots or degree of freedom, with all values standardized to a *per year* scale for consistency. The selection of knot for natural spline has less variation than the degree of freedom choices for smoothing spline. Choices for temperature and humidity are generally similar, given they are both weather related variables, whereas choices for time are more varied. This tabulation provides a reference set for common parameter choices for future studies and help to identify anomalies and special treatment in practice. For example, the choice of 7.7 degree of freedom reported in Castillejos et al. [13] may prompt analysts to seek further justification. By cross comparing with other reporting, some decisions appear ambiguous. For example, in Moolgavkar [55] and Moolgavkar [56], the reported value of 30 and 100 degrees of freedom for time may be understandable for experienced domain researcher, it could be unclear for junior analysts as to whether they apply to the full 9 year period or on a per-year basis. We also observe a different report style from Schwartz [67], where smoothing spline parameters are expressed as a proportion of the data (“5% of the data” and “5% of the data”) rather than fixed numerical value.

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

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

Similarly, Table 6 summarizes the temporal lag choices for PM, temperature, and humidity. For single-day lags, the lags are considered up to 13 days (approximately two weeks). For multi-day averages, 3-day and 5-day averages are most common, although other choices such as 2-4 day average are also observed as in López-Villarrubia et al. [52]:

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

4.3 Paper similarity and clustering

Given the number of decisions reported in Table 4, we focus on the six most common variable-type decisions for calculating paper similarity: parameter choices for time, temperature, and humidity, and temporal lag choices for PM, temperature, and humidity. We also restrict our analysis to papers that report at least three of these six decisions, resulting in 48 papers for the similarity analysis. This ensures that the paper similarity metric is based on a sufficient number of comparable decisions. We use the default text embedding model (BERT) in the `text` package and cosine similarity to compute the similarity score. Sensitivity analysis on different text embedding model is checked in Section 4.4.3. Paper similarity is then calculated as the average of decision similarity for each paper pair. The resulting distance matrix is then used for multi-dimensional scaling (MDS) in Figure 3. The two MDS dimension reveals three clusters correspond to the three smoothing methods used in these analyses: LOESS, natural spline, and smoothing spline. This grouping aligns with the modelling strategies seen in large-scale analysis, such as the U.S. NMMAPS study [63] and the European APHEA [40] and APHEA2 [41] project.

To reconcile these differences, the APHENA project [42] was launched with the aim to "assess the consistency across Europe and North America when estimated using a common analytic protocol and to explore possible explanations for any remaining variation". While multi-dimensional scaling in Figure 3 shows the match of three clusters with three smoothing methods, this is not inconsistent with the APHENA project [42] that the amount of smoothing to have a more important role than the method of smoothing for estimating the effect of PM on public health variables. The similarity metric we proposed focuses on the variation of choices across analyses, without directly assessing how those choices influence results. By pooling decision choices from multiple studies with LLMs, it becomes much easier to reveal common practices and difference in research practices, highlighting decisions that require further sensitivity analyses to assess their impact. The different smoothing methods revealed in Figure 3 are consistent with the analysis by Peng et al. [61] and Touloumi et al. [73] that compares different smoothing methods and rationale for selecting smoothing parameters.

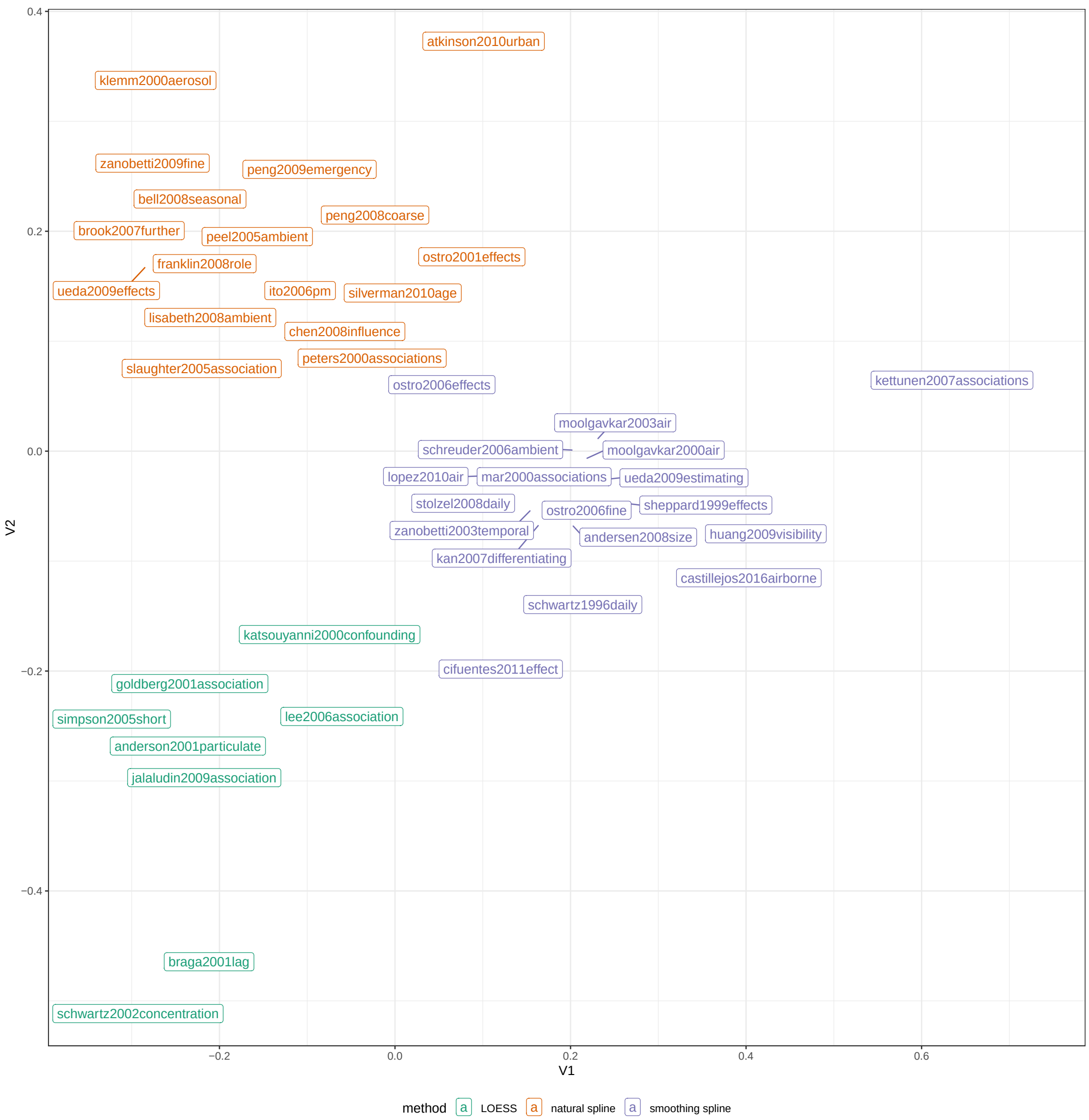

Fig. 3. The multi-dimensional scaling (MDS) based on paper similarity distance for `length(good_pp)` air pollution mortality modelling papers, colored by the smoothing method used. The MDS reveals the three distinct groups of papers, corresponds to LOESS, natural spline, and smoothing spline. These groups corresponds to the different modelling strategies debated in the European and U.S. studies, as documented in the APHENA project [42].

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`) 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 $5 \times 4/2 \times 62 = 620$ possible comparisons for both "reason" and "decisions" fields. Comparisons where the runs produced a different number of decisions were excluded, as this would require manual alignment. After filtering, 449 out of 620 (72%) remained. Table 7 prints the decisions in Andersen et al. [3] across two runs and all the four decisions are identical with no difference.

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

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

Table 8 summarizes the number of differences observed in each pairwise comparison. Among all comparisons, 80% produce the identical text in reason and decision. The discrepancies come from the following two reasons: 1) Gemini extracted different length for the same decision, e.g. in Kan et al. [38], some runs may extract "singleday lag models underestimate the cumulative effect of pollutants on mortality 2day moving average **of current and previous day**

concentrations (lag=01)", while others extract "singleday lag models underestimate the cumulative effect of pollutants on mortality 2day moving average (lag=01)". Similarity, for decisions, some runs yield "10 df for total mortality", while other runs yield "10 df". 2) Gemini fails to extract reasons in some runs but not others, e.g. in Burnett et al. [11], the first run generates NAs in the reasons, but the remaining four runs are identical. In Ueda et al. [74] and Castillejos et al. [13] , 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.

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 Antropic Claude (`claude-3-7-sonnet-latest`) and Google Gemini (`gemini-2.0-flash`). We compare the number of decisions extracted by Claude and Gemini across all 62 papers in Figure 4. 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. While both models extract decisions irrelevant to our analysis, such as sensitivity analyses and secondary analyses, Claude's extractions tend to include more of these irrelevant decisions, examples of these include 1) the definition of "cold day" and "hot day" indicators in Dockery et al. [18] ("defined at the 5th/ 95th percentile"), 2) decisions relate to other pollutants: NO_2, O_3, and SO_2 using a "24 hr average on variable" in Huang et al. [30], and 3) the definition of black smoke and in Katsouyanni et al. [41] for secondary analysis ("restrict to days with BS concentrations below 150 $\mu g/m^2$"). While Gemini also capture these irrelevant decisions, such as "0-4 lag days" for air pollution exposure variables (CO, EC, K_S, NO_2, O_3, OC, Pb, S, SO_2, TC, Zn) in Mar et al. [53]. However, these cases are less frequent than Claude's extraction and has been validated and standardized in Section 4.1.

For both Claude and Gemini, we find they fail to link the general term "weather variables" to the specific weather variables (e.g. Dockery et al. [18] and Burnett et al. [12] for Gemini and Dockery et al. [18] and Katsouyanni et al. [41] for Claude). Although our prompt specified that some decisions may require linking information across sentences and paragraphs to identify the correct variable, this instruction doesn't appear to be applied consistently.

4.4.3 Text model. We have conducted sensitivity analysis on the text model for obtaining the decision similarity score from the Gemini outputs. The tested language models tested include 1) BERT by Google [17], 2) RoBERTa by Facebook AI [51], trained on a larger dataset (160GB v.s. BERT's 15GB), 3) XLNnet by Google Brain [80], and two domain-trained BERT models: 4) sciBERT [5], trained on scientific literature, and 5) bioBERT [46], trained on PubMed and PMC data.

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

5 Discussion

5.1 Large-language models for information extraction

Numerous studies have demonstrate the capability of LLMs in various information extraction tasks [4, 20, 23, 25, 27, 29, 43, 47, 62, 66, 68]. Our work adds to this growing body of evidence by showcasing the effectiveness of LLMs information extraction task, specifically for extracting analytic decisions in scientific literature. While some of the information

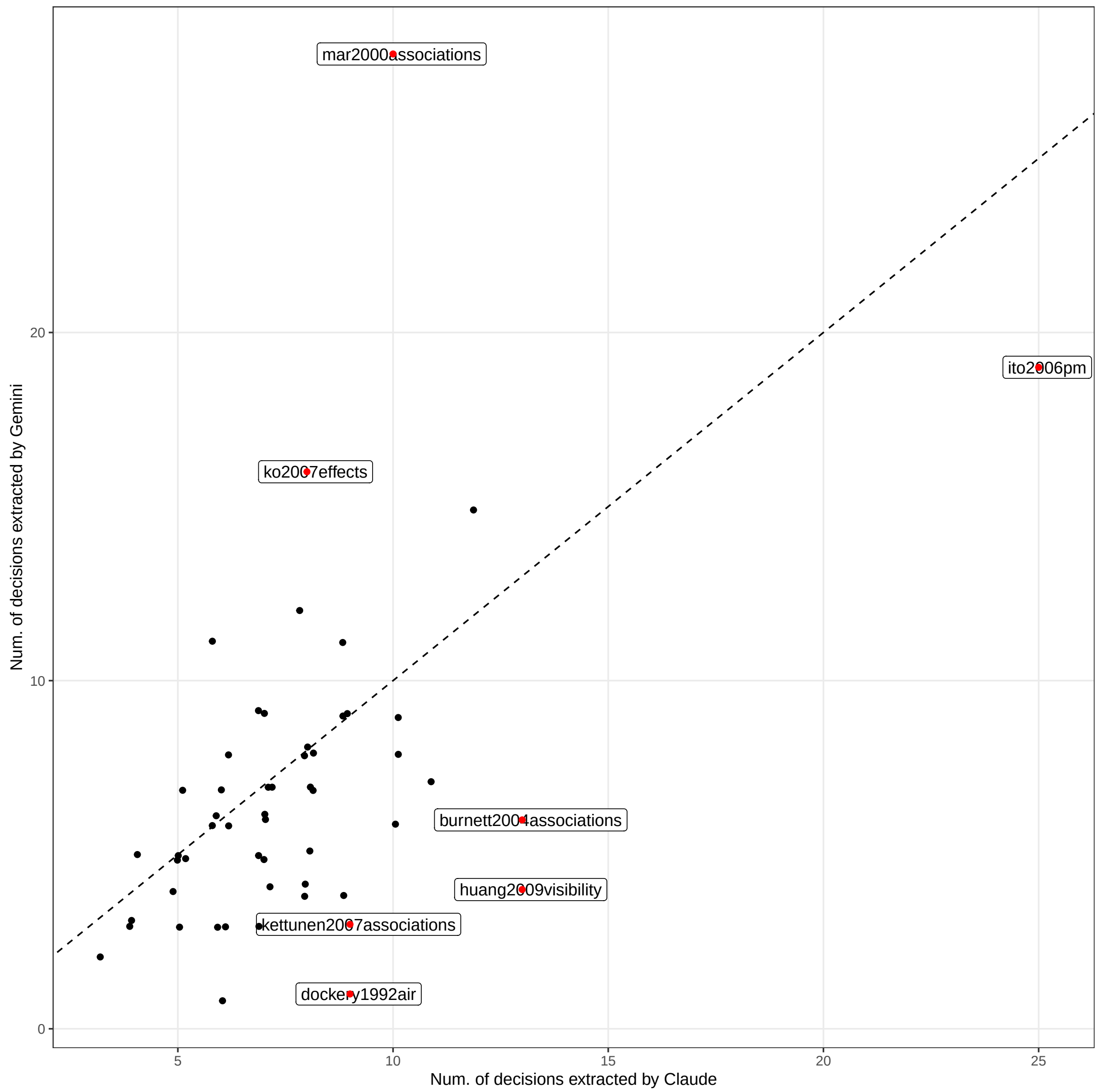

Fig. 4. Comparison of decisions extracted by Claude and Gemini. Each point represents a paper, with the x- and y-axes showing the number of decisions extracted by Claude and Gemini, respectively. The dashed 1:1 line marks where both models extract the same number of decisions. More points fall below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

extraction tasks has a short span of 1-4 tokens, for example in clinical data, our task involves extracting more complex decisions and justification for such analytical decisions, where the justification can span a full sentence. This changes the nature of specific named entity recognition (NER) tasks to a more general information extraction task. Our task also require LLMs to link information across sentences and paragraphs to correctly identify the variable associated with

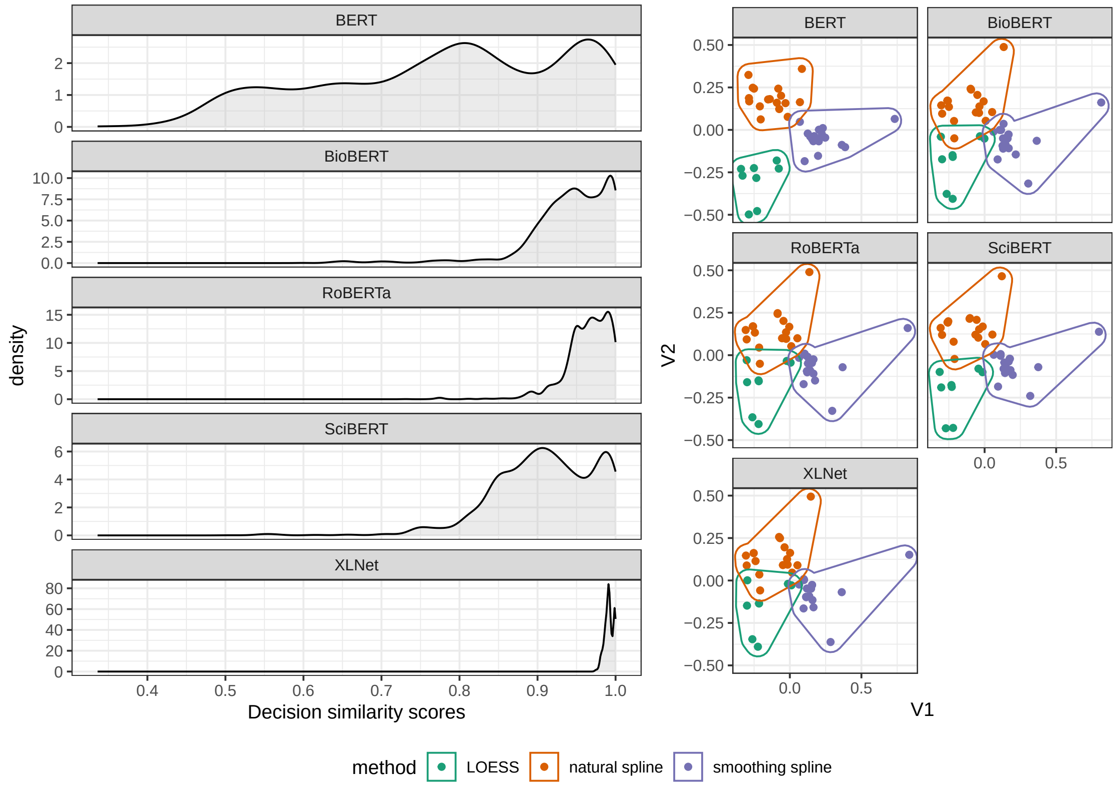

Fig. 5. Distribution of decision similarity (left) and multi-dimensional scaling (MDS) of the paper similarity scores (right) computed for five different text models (BERT, BioBERT, RoBERTa, SciBERT, and XLNet). The default language model, BERT, produces the widest variation across the five models, while 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).

each decision and use reasoning to identify whether a justification provided is indeed a reason specific to the choice of the decision.

While the extraction of decisions from literature could be largely automated with LLMs, manual validations remains essential to ensure the quality of the extracted decisions for further analysis. Most existing applications compares the LLM outputs with human-annotated samples to demonstrate the effectiveness of LLM extraction through the F1 score from precision and recall. However, this approach requires a labelled dataset for training and testing, which may not be feasible for many applications. In our application, we do not have a labelled decision dataset for training and testing. Instead, we focus on validating the LLM outputs through an interactive shiny application that allows users to review and validate each extracted decision. We also use a secondary LLM (Claude) to standardize the temporal lag choices into two categories: multi-day average and single-day lags, to standardize authors use different expressions to describe temporal lag choices. While the effectiveness with LLM to automate information extraction, it is still an open question on how to validate its output in the absence of a labelled dataset.

Using a default temperature of 1 and instructing the model to extract original text rather than paraphrase, we find hallucination is not a major issue with Claude and Gemini for this application. Given the probabilistic nature of LLM outputs, we also conduct sensitivity analysis on the reproducibility of the outputs and variation among different model providers (Claude and Gemini). We find that our information extraction task in general is stable across multiple runs with the same model and different models perform similarly in terms of the number of decisions extracted, although the specific decisions extracted may differ.

While prompt engineering is used in this work to optimize the prompt for decision extraction, an alternative is to fine-tune a local model to improve LLM performance. Such approach could be beneficial for a systematic literature review, although it would require a labelled decision dataset for training and significantly more training efforts.

5.2 Extracting other types of decisions

As a demonstration, we focus on the modelling decision for the baseline model in the air pollution epidemiology literature. Analyses in this fields often fit multiple models for different health outcomes. Other models, such as distributed lag models and multi-pollutant models are also commonly used to estimate relative risks and the interaction among pollutants. These factors increase the complexity of the decision extraction for LLM, as for additional models,authors often describe only the differences from the baseline model specification, assuming other decisions remain unchanged. 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, decisions in data pre-processing are also interesting to compare. For example, in Braga et al. [10], air pollution measures are aggregated from multiple PM10 monitors within the same location into a single value. Different decisions on how values are extracted, imputed, and aggregated are also shown to affect the results. However, these decisions are often not well documented in the literature than the modelling decisions, making it difficult for LLMs to extract them. Proper documentation and reporting of these decisions in future research are needed before our workflow could be applied to pre-processing decisions.

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.

5.3 Generalizability of the workflow

Our workflow is scalable and generalizable. In principle, one can take a random set of applied papers for our workflow. However, insights about the data analysis practices are more likely to be learnt when papers share some similarities, for example literature on teh same topic but from different researchers can compare practices, papers use the same methodology but from different fields enables us to compare practices across fields, or even paper with the same variables used and how they are used in different fields.

The prompt for LLMs to extract decisions will need to be customized for individual application of our workflow. The general LLM prompt structure of separating task and rules can be retained and the data structure for recording decisions can be retained. Users may want to further customize the examples throughout the prompt to suit their specific applications. The shiny application for interactively validating and standardizing decisions can be reused for different applications. Calculation of paper similarity requires comparing decisions of the same variable and type among paper pairs. For papers with different levels of similarities, the number of comparable decisions may be limited and diagnostic functions in the R package can be used to view the decision between paper pair side by side or provide summary statistics on the number of decisions available for calculating the paper similarities. Uncertainty visualization could be used to highlight the confidence in the similarity metric based on the number of comparable decisions.

As a new method to collect analytic decision data from literature, our work can connect to meta-analysis to assess how different decisions affect the results and also in general literature search and recommendation applications to find similar papers based on the decisions made in the analysis.

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 through comparing the similarities among decisions and the similarity metric can be used as a distance to cluster papers by their decision choices and visualization with dimension reduction algorithms, such as multidimensional scaling. We applied this pipeline to a set of air pollution modelling literature that associates daily particulate matter and daily mortality and hospital admission. From the extracted modelling decisions, we identify the most common decision choices in this type of analysis and the paper similarity score calculation revealed the three clusters of paper corresponding to different modelling strategies. These findings are all consistent with the general understanding of the field, as documented in the APHENA project [42] and other methodological comparison studies [61, 73].

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

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