Module 3 Track 1 Paper: Comparing Urban AI Governance Strategies Through Topic Modeling: Quantitative Analysis of City-wide AI Policies in the United States

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Tools utilizesd: pyLDAvis, Gensim, pdfminer, pandas and matplotlib Python libraries for data cleaning, analysis and vizualization, GitHub Copilot for code debugging, Grammarly for writing assistance.

Abstract

In recent years, many major U.S. cities have introduced municipal-level guidelines or policies related to the use of artificial intelligence (AI) within city agencies. While these policies generally focus on transparency, bias, equity, and fairness issues related to AI, the emphasis placed on these topics varies across jurisdictions. This study examines how different cities frame AI and AI-related issues in their documents using Natural Language Processing (NLP) topic modeling of AI policies. Documents from nine US cities were analyzed using a Latent Dirichlet Allocation probabilistic model in order to extrant latent topics. This approach enables analysis of the current state of urban AI governance in the US and highlights shared concerns and key differences across cities.

Keywords: *urban AI, AI governance, AI policies, Nature Language Processing, topic modeling*

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1 Introduction

In recent years, artificial intelligence (AI) has become a major topic of public discussion due to its potential to transform the nature of modern work through advances in task automation, as well as due to concerns about biases and risks embedded in the technology. As more people rely on large language models and chatbots like ChatGPT to automate work tasks (Tyson and Zysman, 2022), discussions about the potential consequences and ways to regulate them have become important, especially in the public sector.

However, due to the novel nature of the technology, little effort has been made to produce regulations on AI usage on a broader level. Consequently, many major U.S. cities have introduced municipal-level guidelines or policies related to the use of AI within their city agencies (David et al., 2024). These policies essentially outline general guidelines for city employees on how to use AI models and the precautions to take to avoid its pitfalls. While these policies generally focus on transparency, bias, equity, and fairness issues in AI, the emphasis placed on these topics varies across jurisdictions.

This study examines how different United States (US) cities frame AI and AI-related issues. The research question could be summarized as follows: What are the major topics in urban AI policy documents, and how are cities similar or different in terms of framing AI-related issues? To answer this question, latent topic modeling was conducted using the Latent Dirichlet Allocation (LDA) probabilistic model on a corpus of AI policies and guidelines from nine U.S. cities that have enacted such documents. The analysis reveals the primary topics discussed in these documents and highlights shared themes and distinct focuses of different jurisdictions. More broadly, this study highlights the state of urban AI governance and the priorities that cities follow when introducing and implementing new technology (Caprotti et al., 2024).

This paper is structured as follows: Section 1 outlines the background of the study and the research question that guides it. Section 2 describes the data and methods, with a specific focus on the data collection and cleaning techniques used, as well as the topic modeling approach utilized. Section 3 presents the results of the topic modeling by describing and interpreting the potential topics derived from the corpus and how the policies of different cities vary across the derived topics. Lastly, Section 4 offers a discussion of the results, outlines the study's main limitations, and suggests directions for future research.

2 Data and Methods

2.1 Data Collection

Table 1: Municipal AI policy documents overview

City	State	Document name	Pages
Salt Lake City	Utah	Use of Generative Artificial Intelligence (Article E, 52-13E)	2
Cambridge	Massachusetts	City of Cambridge Guidelines on Using Generative Artificial Intelligence (AI)	7
San José	California	Artificial Intelligence (AI) Policy 1.7.12 — City Administrative Policy Manual	4
San Francisco	California	San Francisco Generative AI Guidelines (2025)	10
Tempe	Arizona	Ethical Artificial Intelligence (AI) Policy	3
Washington	District of Columbia	AI/ML Governance Policy (OCTO)	4
Lebanon	New Hampshire	Administrative Policies & Procedures — Use of Artificial Intelligence (ADM-143)	7
Boston	Massachusetts	City of Boston Interim Guidelines for Using Generative AI (v1.1)	10
Long Beach	California	City of Long Beach Generative AI Guidance (v1.3)	10

The data, in the form of AI policies, was collected manually by searching for and retrieving relevant documents. Before proceeding, it is important to note the distinction between the types of documents collected. As AI becomes a significant concern for many jurisdictions worldwide, various documents related to it have been published. However, as outlined in the research question in the previous section, this study focuses on policies detailing guidelines for city agencies' use of AI, rather than other aspects. Therefore, my analysis does not include documents outlining broader AI policies, such as the New York City Artificial Intelligence Action Plan. This plan does not provide specific guidelines; rather, it describes the city's broader AI development and management policy, and therefore is irreleant for this study.

I initially used Google Search to find news and other publicly available information on cities that implemented AI policies, using the keyword "AI policies US cities." Then, I manually searched for specific cities that I identified as having an AI policy (e.g., "AI policy Boston"). Most PDF documents were conveniently stored in the open-source Digital Government Hub library (Beeck Center for Social Impact + Innovation, Georgetown University, n.d.) and were downloaded from there. Documents unavailable in the library were downloaded from the cities' official websites.

Given the novelty of AI as a public policy issue, the collected data were represented by various legal documents. In some cases, there were AI guidelines, or internal policies, for government employees that were authored by the city's Chief Information Officer or a similar office. In other instances, the documents were executive orders signed by the city's mayor.

In total, I collected nine AI policy documents in PDF format from US cities. A complete list of the documents, including the city, the document's title, and other descriptive information, is presented in the table 1. In aggregate, I collected 56 pages of AI policy documents that constitues corpus for topic modeling.

2.2 Data Cleaning

After collecting PDFs of the documents, I utilize the PDFMiner library in Python to extract the text from each of the 56 pages. Then, I normalized the text data by addressing Unicode and spacing issues and by removing headers, page footers, web page and email addresses, numbers, punctuation, and standalone letters. I also transformed text into lowercase.

Since the dataset of nine documents and 56 pages is relatively small for a topic modeling approach, I treat individual paragraphs as "documents" in the NLP sense, referring to distinct units of text analyzed. This enabled full-scale topic modeling using the LDA model, which is described in the next section and yielded satisfactory results. Technically, it is done by separating the text of each page using double new lines sign. The average paragraph or documents length is 20 characters. Additionally, I lemmatize each word in the corpus, reducing it to its base form, to avoid instances where the model treats the same word as different units based on differences in form.

Before applying the LDA model to the cleaned data, I generate a stopword dictionary based on the standard English stopword set from scikit-learn library (Pedregosa et al., 2011), which includes standard English words, as well as context-specific words such as names of cities, policy-specific words (e.g., guidelines), dates, acronyms, and names of AI vendors (e.g., Microsoft or ChatGPT). I also use a frequent words counter to select words that do not add semantic value to the corpus (e.g., "generative," "intelligence," and "understand") and filter them out. These heuristics improve the robustness of the model by eliminating words with low semantic meaning. Since these words are expected to be present due to the nature of the collected data, they do not signify relevant topics of the corpus.

2.3 LDA Modeling

After cleaning the data, I proceeded to conduct Latent Dirichlet Allocation (LDA), a standard modeling apporach in NLP scholarship, using the Gensim and pyLDAvis libraries. As summarized by Kalepalli et al. (2020, p. 1247), LDA is "probabilistic model and an unsupervised learning algorithm, where the documents are represented as random mixtures over latent topics, where specific topics are characterized by a distribution over words." Essentially, LDA classifies documents according to topics derived from a dataset (corpus) by treating each word as a unit of meaning that determines its relationship to a particular topic.

Before applying the model, I vectorized the cleaned data using CountVectorizer in the scikit-learn library (Pedregosa et al., 2011) to transform the text into a matrix of token counts. This creates a vocabulary of all unique words in the corpus and represents each document (paragraph) as a vector. Next, I generate an unsupervised model using Gensim library (Řehůřek and Sojka, 2010). I manually selected

Table 2: Latent topics derived from the LDA model

Topic	Keywords
Topic 1	datum, public, human, risk, responsible
Topic 2	review, public, risk, number, security
Topic 3	prompt, datum, employee, decision, text
Topic 4	datum, resource, review, bias, protect
Topic 5	privacy, datum, risk, description, public

the number of topics, which was equal to five, via an iterative process of testing and refinement. Manual selection of the number of topics was employed instead of automatic optimization based on a particular metric because any automatic optimization of topic selection would not be robust enough due to the small number of documents in the corpus and the small size of the documents themselves. Furthermore, studies have shown that there is no reliable way to evaluate the effectiveness of topic modeling techniques because existing metrics, such as perplexity or log-likelihood, as they do not correlate with human judgment based on manual reviews (Chang et al., 2009).

3 Results

In this section, I interpret the results of LDA topic modeling using latent topic output table and a series of additional visualizations. These visualizations highlight how derived topics are distributed across selected AI policies of US cities.

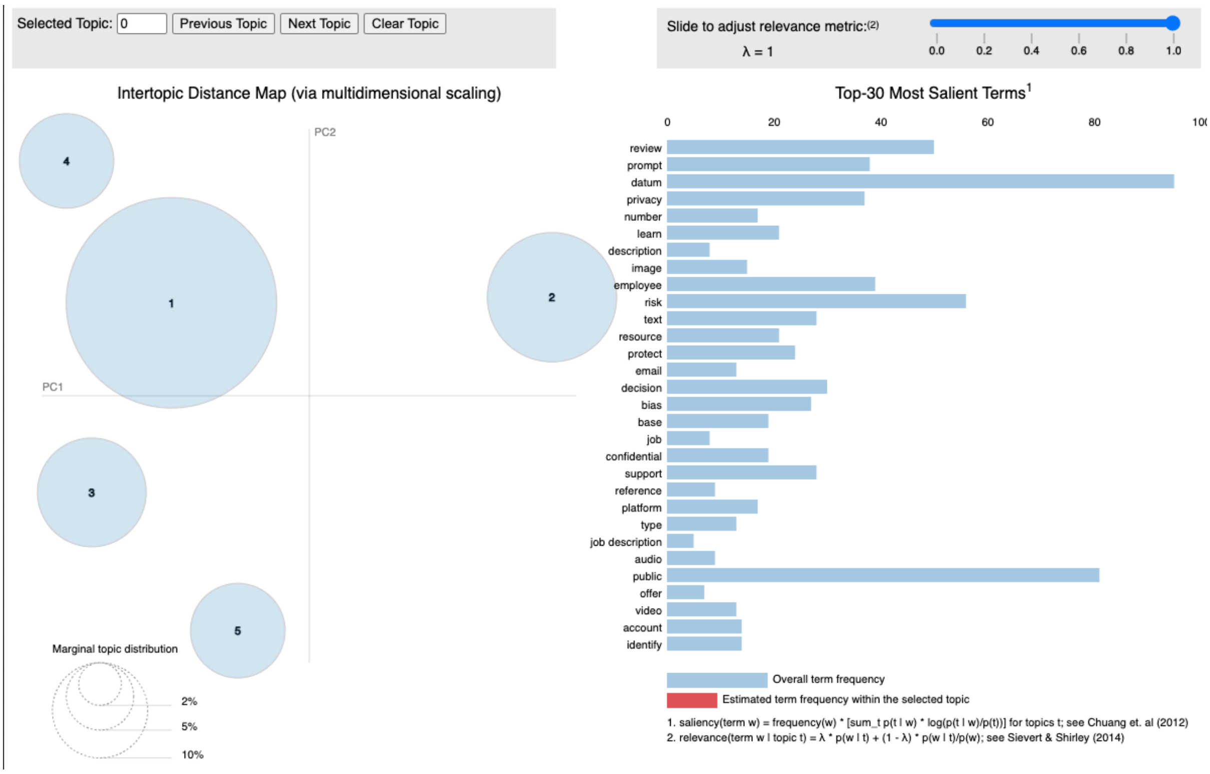


Figure 1: pyLDAvis graphical user interface (GUI) showing Intertopic Distance Map and Top-30 Most Salient Terms.

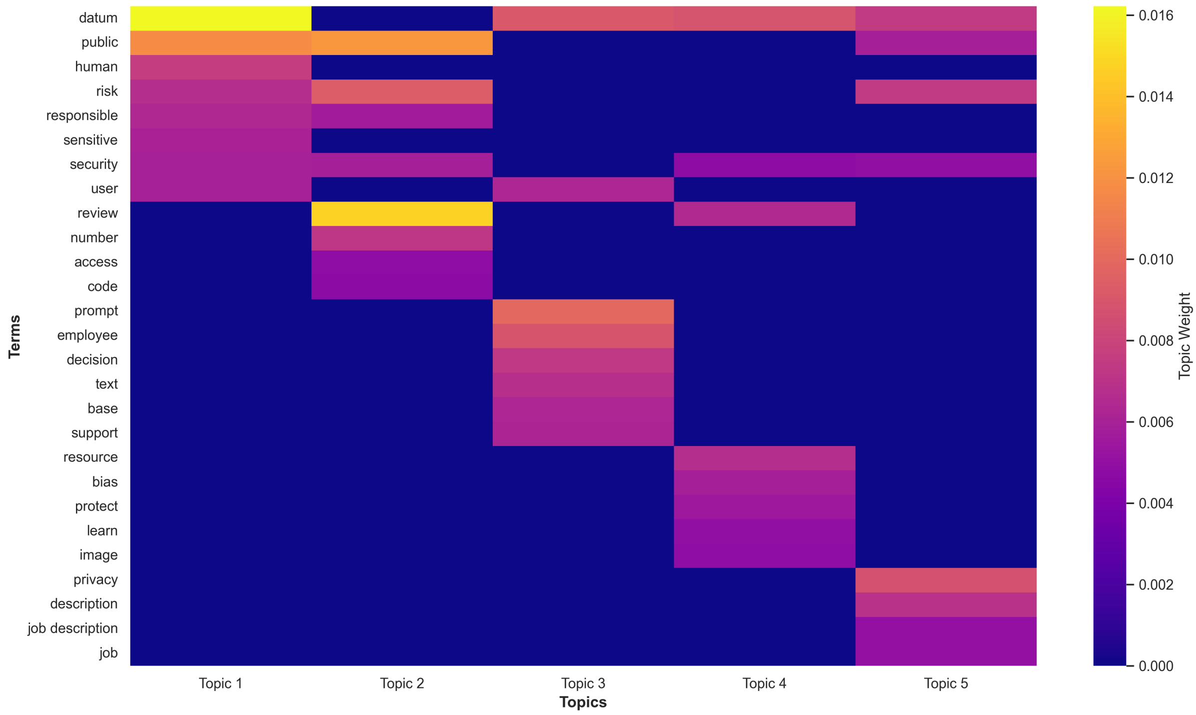


Figure 2: Topic-term distribution matrix showing the top eight most probable terms for each of the five latent topics extracted from urban AI policy documents. Cell intensity represents the probability weight of each term within its respective topic, computed using LDA.

3.1 Topic Modeling

Table 2 shows topics derived from the corpus. Topic 1 consists of keywords related to data (datum is its lemma), the public, humans, and responsibility. This could potentially be attributed to discussions about the risks of using AI and the resulting necessity for human responsibility when entering data into AI models. Topic 2 consists of keywords related to review, risk, numbers, and security. These keywords could be interpreted as discussions about the security risks associated with AI models. Topic 3 uses keywords related to prompts, data, decisions, and text. Therefore, it resembles discussions about prompt engineering when dealing with AI models, as well as the idea that human employees should make final decisions. Topic 4 includes keywords such as data, resource, review, and bias, resembling discussions about reviewing the outputs of AI models for potential biases and protecting government data. Topic 5 contains similar keywords and resembles discussions about privacy and public risks associated with AI models.

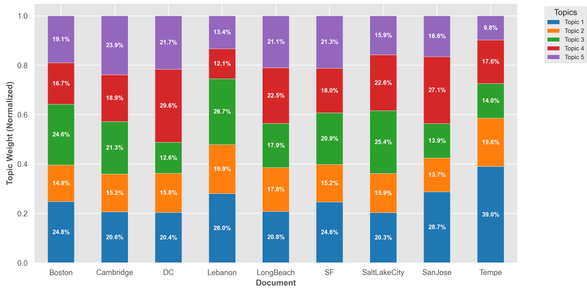
Figure 1, generated using the pyLDAvis Sievert and Shirley, 2014 graphical user interface, shows the intertopic distance map. It highlights that topics 1, 3, 4, and 5 are somewhat similar while topic 2 is significantly different. Additionally, it illustrates that Topic 1 is the most significant topic within the analyzed documents. Furthermore, the figure shows that ”data” and ”public” are among the most salient keywords within the corpus.

Figure 2 that data, public, user, and security are among the keywords that are most present in the derived topics. It also highlights that there are keywords specific to each topic. For example, the words review and assess are specific to Topic 2, while prompt, employee, and decision are specific to Topic 3.

3.2 Distribution of topics within documents

As outlined in the research question, this paper is primarily interested in topics derived from the LDA model and their distribution among each city's AI policy documents. The figure 3a illustrates this distribution. Topic 1, which is related to potential risks and responsibility, is highly prevalent across all cities' policies and especially so in Tempe's policy. Topic 2, which focuses on security and risks, is

(a) Document-topic probability distribution matrix revealing thematic variation across analyzed documents. Each cell represents the mean topic probability for all text segments within a document. Annotated values indicate topic probability on a 0–1 scale.



(b) Normalized topic composition across municipal AI governance documents, displayed as stacked proportions summing to 100% per document. Each colored segment represents the relative prevalence of one of five latent topics within a document's policy corpus.

Figure 3: Topic distribution across analyzed municipal AI governance documents. (a) Document-topic probability distribution matrix. (b) Normalized topic composition across documents.

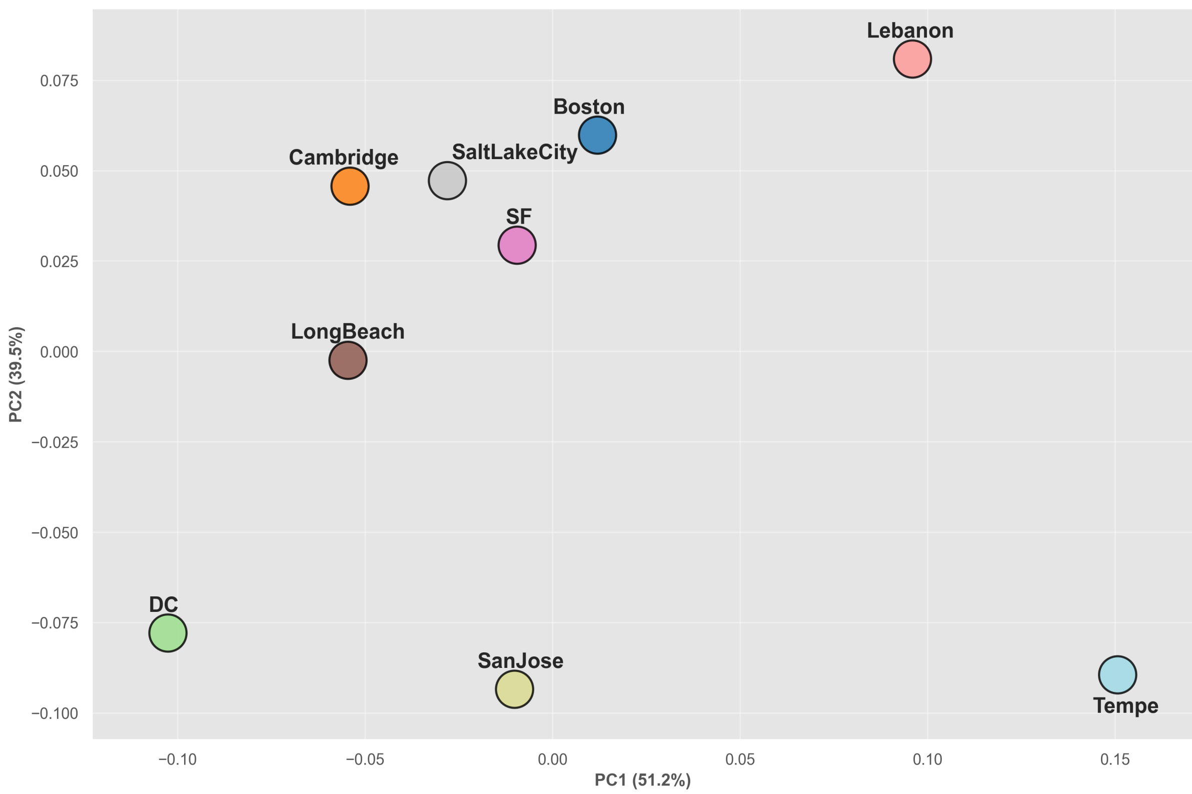


Figure 4: Principal Component Analysis (PCA) projection of document similarity in topic space. Each point represents one of the city's AI policies, positioned in a 2D coordinate system derived from the first two principal components of the topic distribution matrix. Axis labels indicate the fraction of variance explained by each component.

especially prevalent in Tempe's and Lebanon's policies. Topic 3, which focuses on prompts and decisions, is not important in the District of Columbia, San Jose, or Temple but is important in Lebanon, Salt Lake City, San Francisco, Cambridge, and Boston. Topic 4, which focuses on reviews and biases, is critical in the District of Columbia and San Jose but rarely mentioned in Lebanon. Topic 5, which focuses on privacy and risks, is important in most jurisdictions except Lebanon and Tempe.

Furthermore, figure 3b the proportion of policy dedicated to each topic. Topics 1 and 3 are the most significant in Boston and Lebanon. In Cambridge, Topic 5 is dominant, while Topic 4 is dominant in DC's policy. In the policies of Long Beach and San Francisco, the topics are distributed somewhat equally. Topic 3 is dominant in Salt Lake City, while topic 4 is dominant in San Jose. Lastly, topic 1 significantly dominates the policy of Tempe, constituting more than one-third of it.

Finally, we can compare the similarities in the AI policies of different cities. The figure 4 shows that, in terms of utilized topics and keywords, five of the selected cities, Long Beach, Cambridge, Salt Lake City, Boston, and San Francisco, are very similar in terms of topic and keyword distribution. However, Lebanon, Washington, D.C., San Jose, and Tempe are vastly different.

4 Discussion and Conclusion

4.1 Discussion

This study uses Latent Dirichlet allocation (LDA) topic modeling on a corpus of nine urban AI policy documents from cities in the United States. By deriving main topics from the analyzed corpus, I deduce five main topics of the corpus: risks and human responsibility, need for review of AI models' outputs and focus on security, prompt engineering, and the fact that humans should make decisions rather than AI models, focus on biases and data, and privacy and risk to public when dealing with AI models. Furthermore, I demonstrate which topics dominate various AI guideline documents and how some cities share topics while prioritizing different aspects when designing policies related to AI implementation within city agencies. Additionally, I identify general themes that recur across all documents, such as issues related to data, security, and public responsibility.

Overall, this analysis highlights the state of urban AI governance in the United States. Numerous issues and implications arise when city agency employees use AI to perform work tasks, and cities address these issues in different ways. Different policy focuses might yield different outcomes; therefore, it is essential to consider how policy documents frame AI and AI-related issues.

4.2 Limitations

The results of the study should be interpreted in light of its limitations. First, the study used a small set of policy documents collected via an iterative internet search. The small size of the analyzed corpus limits our findings to documents that are actively discussed, omitting other AI policies and guidelines. Second, the study focused on AI policies in the United States even though the introduction and implementation of AI in the workplace is a global issue addressed across many jurisdictions worldwide. Third, while I analyzed the distribution of topics across cities' policies, I did not analyze what might have caused these differences.

4.3 Directions for Future Research

These limitations present potential avenues for future research. Future studies should focus on more systematically collecting data before conducting topic modeling and include a wider variety of AI-related documents in the analysis. They should also consider alternative approaches to topic modeling, such as BERTopic (Grootendorst, 2022), which utilize more cutting-edge deep-learning techniques. Additionally, scholarship should focus on AI policies and guidelines outside the US. Lastly, future scholarship would benefit from analyzing the topics in the collected documents and the reasons behind differences in topics across jurisdictions. For example, these studies could address questions related to the political orientation of a city's population and its current administration (e.g., Republican or Democrat), as well as other factors that might influence the design of AI policy.

Data and Code Availability

The data and code supporting the findings of this study are available in the following GitHub Repository: https://github.com/temapankin/UrbanAI-TopicModellng.

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