Public Conceptions Of Comparative Health Systems

Background

Social imaginaries shape how groups interpret social issues and navigate their shared existence. They are dynamic frameworks that bridge gaps in understanding and help to make sense of familiar and unfamiliar issues. Complex health systems are seldom fully comprehended, and even more infrequently experienced in a comparative context, as few individuals receive health services in different countries. YouTube discussions reflect social imaginaries of health systems. Can these imaginaries evolve as digital communities engage with diverse perspectives and gain insights from individuals rarely encountered in everyday life—medical tourists, expats, or foreign nationals sharing information on medical costs and access?

Study Objective

The purpose of this study is to evaluate social media comments in response to 53 YouTube videos about the U.S. healthcare system: newscasts, full-length documentaries, political satire, and stand-up comedy from 2014-2023. The focus is on commenters who shared comparative analyses of international health systems, based on firsthand experiences or secondhand accounts. The study addressed these questions:

Question 1: How prevalent are health system comparisons? Can they be extracted with AI?

Question 2: Which healthcare systems are compared to the U.S. system?

Question 3: What insights do the health system comparisons provide?

METHODS

STEP 1.
Video Selection:
We selected 53 videos from 17 U.S.-based media outlets based on the following criteria: uploaded to YouTube between 2014 and 2023, 100K+ views, 800+ comments (as of August 28, 2023), and from channels belonging to news, educational, or entertainment organizations.

STEP 2.
Classification:
A Dataframe (DF) of 34,499 comments was processed with a prompt-engineered method claude-3-haiku-20240307 LLM. Each comment was classified as "informant" or "non-informant." Informant comments were then coded for "cost," "access," and "regional mentions" with the labels stored in a Pandas DF for analysis.

STEP 3.
Reliability Analysis:
Informant posts were manually verified to identify false positives and negatives. A confusion matrix was created followed by calculations of Sensitivity, Specificity, Precision, Negative Predictive Value, Accuracy, and the F1 harmonic score to evaluate the model's efficacy and balance.

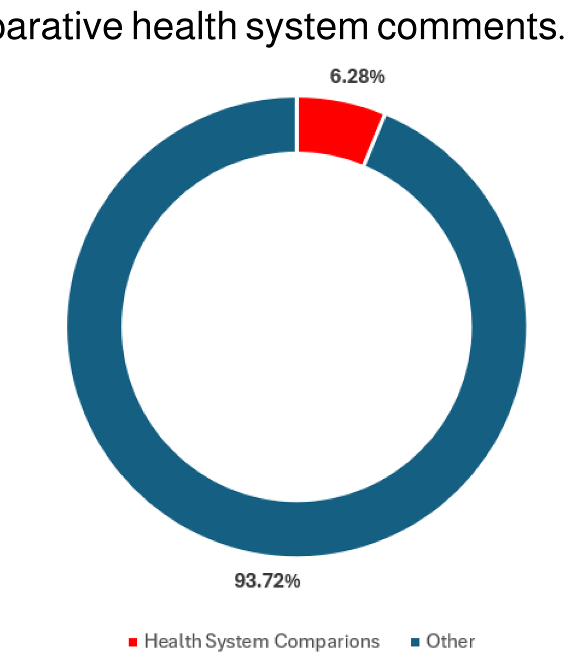
STEP 4.
Co-occurrence Network:
VOSviewer was used to extract terms (nouns and noun phrases) from 179193 comments. NLP-extracted similar terms were merged and irrelevant terms filtered out. The map shows 323 terms appearing in at least 60 comments.

STEP 5.
Overlays for health system comparisons based on cost & access:
Classifications by LLM were converted into scores to visualize the distribution of characteristics of interest across the mapped terms. Visual layers color for each term based on its mean standardized score (in SD units, as compared to all terms' mean).

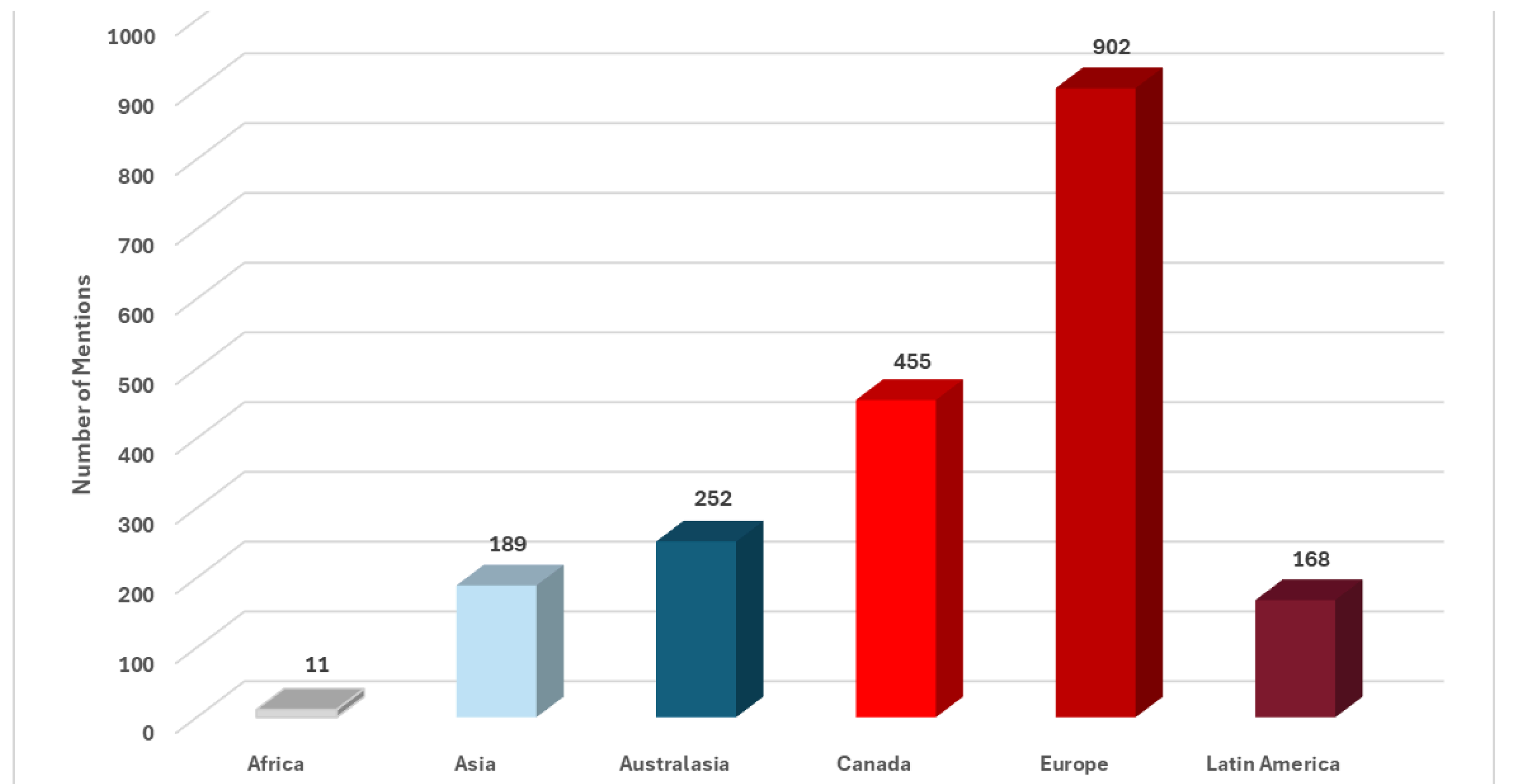
STEP 6.
Descriptive & Semantic Analysis:
Analyzed network nodes, nouns and noun phrases extracted from comments. Identified nodes that scored high (in SD units) on health system comparisons, cost-based comparisons and based on access to care. Identified regions and countries used in health system comparisons.

6% of Comments Were About Healthsystem Comparisons

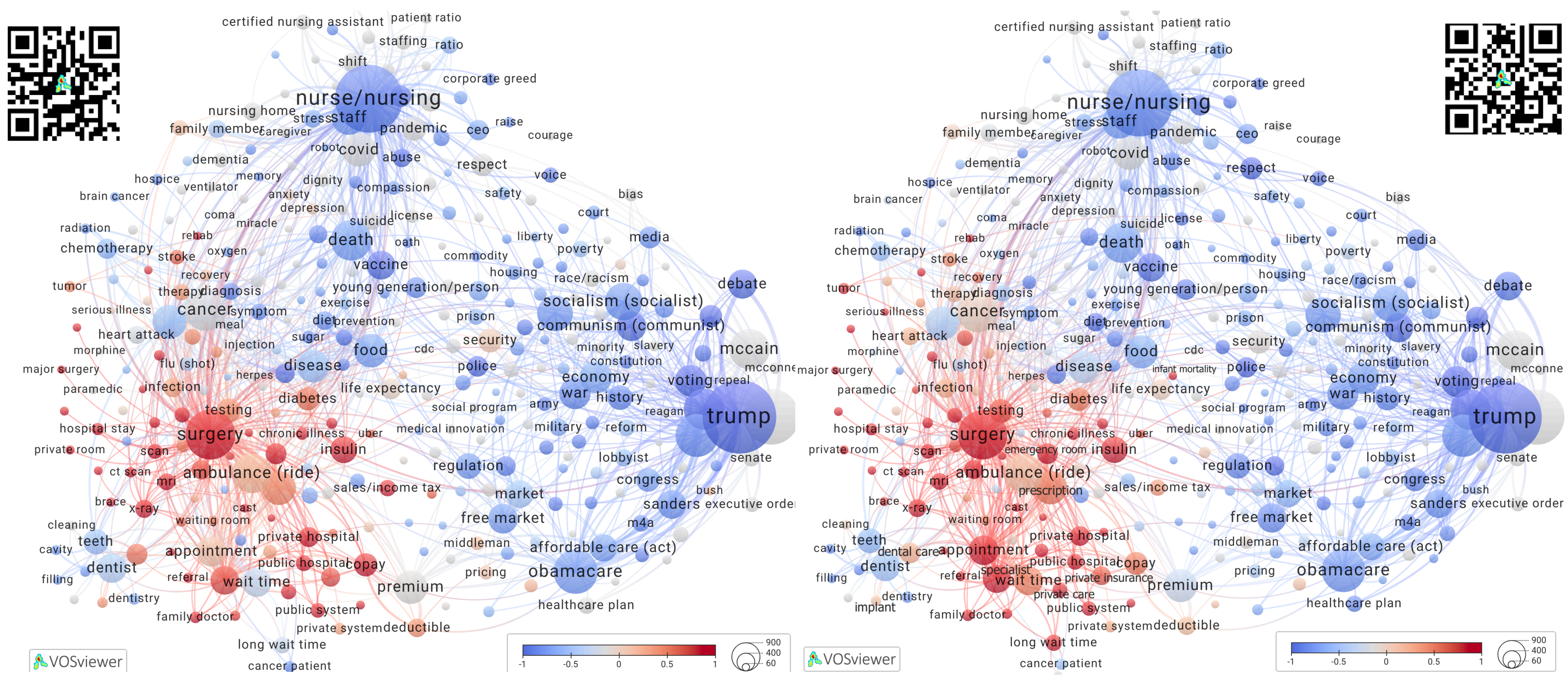
2165 comparative health systems comments were identified in the first 34500 comments processed by LLM. Given the total corpus size, there is a potential to build a dataset of over 10K comparative health system comments.



Non-U.S. Mentions in 2165 Comments about Comparative Health Systems



Health Systems Were Compared on Cost (left) & Access (right), a Terms Co-Occurrence Map



Global comparisons tend to revolve around healthcare costs and access to services. They rarely extend into ideological, political, or healthcare workforce discussions. LLM classifications of comments about comparative health systems can help augment human coding.

Confusion Matrix Claude-3-haiku-20240307 LLM vs. Manual Coding of Comparative Health System Informants

LLM	Manual Coding: Informant	Manual Coding: Other	Total
	N	N	N
Informant	204	2	206
Other	0	94	94
Total	204	96	300

Performance Table

Measure	Calculation	Formula
Sensitivity (Recall)	0.98	True Positive/ (True Positive + False Negative)
Specificity	0.99	True Negative/ (True Negative + False Negative)
Precision	1.00	True Positive/ (True Positive + False Positive)
Negative Predictive Value	0.99	True Negative/ (True Negative + False Negative)
Accuracy	0.99	(True Positive + True Negative)/ (True Positive + True Negative + False Positive + True Negative)
F1 Score	0.99	2 x [(Precision x Recall) / (Precision + Recall)]

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