Selective Sympathy?
Media Coverage, Public Opinion, and Mobilization in the Gaza War

Ala Alrababah, William Marble, Salma Mousa, Alexandra Siegel, and Michelle Torres

July 17, 2025

DISCLAIMER

- Not your traditional bulletproof Polmeth paper

- Not your traditional bulletproof Polmeth paper
- Early draft with TONS of imperfections

- Not your traditional bulletproof Polmeth paper
- Early draft with TONS of imperfections
- Not the case that we started working 2 weeks before the deadline
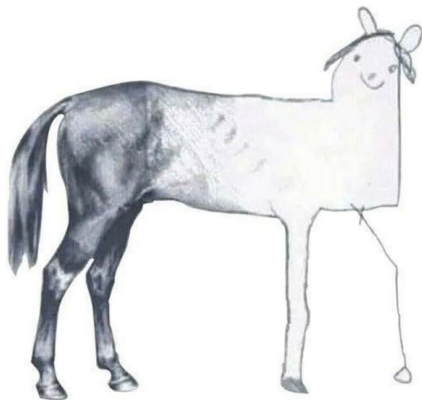
- Not your traditional bulletproof Polmeth paper
- Early draft with TONS of imperfections
- Not the case that we started working 2 weeks before the deadline
- But rather a series of unfortunate events and roadblocks...

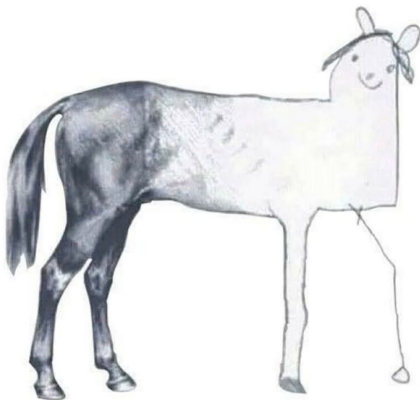# VISUAL REPRESENTATION OF THIS PROJECT (SO FAR)

VISUAL REPRESENTATION OF THIS PROJECT (SO FAR)

(and overview of this talk)

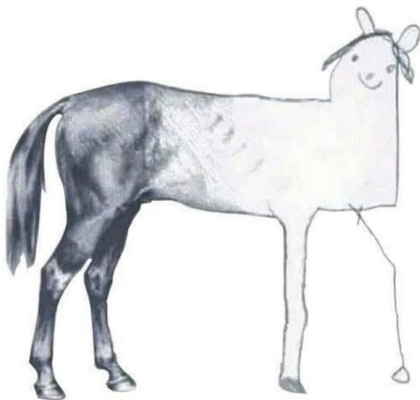## VISUAL REPRESENTATION OF THIS PROJECT (SO FAR)

(and overview of this talk)

Takeaway: we are looking for any and all types of feedback!

VISUAL REPRESENTATION OF THIS PROJECT (SO FAR)

(and overview of this talk)

Takeaway: we are looking for any and all types of feedback!
Now back to serious business.

REAL ROADMAP

REAL ROADMAP

1 Motivation and research questions

2 Original empirical approach

3 Challenges and roadblocks
- Tagging and classification
- Interpretation of quantities of interest

4 What we did
- Methodological decisions
- Results

MOTIVATION

MOTIVATION

Event: On April 13, 2025, with less than a thirty-minute evacuation warning, Israel dropped two bombs on Gaza City's al-Ahli Arab Hospital, killing at least one child.

MOTIVATION

Event: On April 13, 2025, with less than a thirty-minute evacuation warning, Israel dropped two bombs on Gaza City's al-Ahli Arab Hospital, killing at least one child.

MOTIVATION

Event: On April 13, 2025, with less than a thirty-minute evacuation warning, Israel dropped two bombs on Gaza City's al-Ahli Arab Hospital, killing at least one child.

ALJAZEERA   News ⌄   Middle East   Explained   Opinion   Sport   Vic

Israel-Palestine conflict ›   Live updates   What's in Trump's ceasefire proposal?   Hunger, de
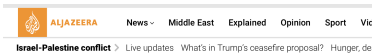
News | Israel-Palestine conflict

Israeli forces bomb al-Ahli Hospital in Gaza, forcing patients to flee

The missile destroyed parts of the hospital, including its emergency department.

FRANCE 24   HOME   SHOWS   NEWSFEED   LIVE

FRANCE   AFRICA   MIDDLE EAST   AMERICAS   EUROPE   ASIA-PACIFIC

WHO says child dies after Israel strike hits Gaza hospital

Gaza City (Palestinian Territories) (AFP) – **An Israeli air strike Sunday hit one of Gaza's few functioning hospitals, resulting in the death of a child according to the World Health Organization, as Israel warned it would expand its offensive if Hamas does not release hostages.**

MOTIVATION

Event: On April 13, 2025, with less than a thirty-minute evacuation warning, Israel dropped two bombs on Gaza City's al-Ahli Arab Hospital, killing at least one child.

AL JAZEERA   News ∨   Middle East   Explained   Opinion   Sport   Vi∢

Israel-Palestine conflict ❯ Live updates   What's in Trump's ceasefire proposal?   Hunger, de

News | Israel-Palestine conflict

Israeli forces bomb al-Ahli Hospital in Gaza, forcing patients to flee

The missile destroyed parts of the hospital, including its emergency department.

FRANCE 24   HOME   SHOWS   ⊘ NEWSFEED   ☐ LIVE
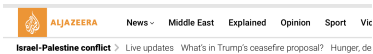
FRANCE   AFRICA   MIDDLE EAST   AMERICAS   EUROPE   ASIA-PACIFIC

WHO says child dies after Israel strike hits Gaza hospital

Gaza City (Palestinian Territories) (AFP) – **An Israeli air strike Sunday hit one of Gaza's few functioning hospitals, resulting in the death of a child according to the World Health Organization, as Israel warned it would expand its offensive if Hamas does not release hostages.**

B B C

Israeli air strike destroys part of last fully functional hospital in Gaza City

13 April 2025

Share ❮   Save ☐

MOTIVATION

Event: On April 13, 2025, with less than a thirty-minute evacuation warning, Israel dropped two bombs on Gaza City's al-Ahli Arab Hospital, killing at least one child.

ALJAZEERA News Middle East Explained Opinion Sport Vic

Israel-Palestine conflict Live updates What's in Trump's ceasefire proposal? Hunger, de

News | Israel-Palestine conflict

Israeli forces bomb al-Ahli Hospital in Gaza, forcing patients to flee

The missile destroyed parts of the hospital, including its emergency department.

FRANCE 24 HOME SHOWS NEWSFEED LIVE

FRANCE AFRICA MIDDLE EAST AMERICAS EUROPE ASIA-PACIFIC

WHO says child dies after Israel strike hits Gaza hospital

Gaza City (Palestinian Territories) (AFP) – An Israeli air strike Sunday hit one of Gaza's few functioning hospitals, resulting in the death of a child according to the World Health Organization, as Israel warned it would expand its offensive if Hamas does not release hostages.

B B C

Israeli air strike destroys part of last fully functional hospital in Gaza City

13 April 2025   Share Save

Israel Strikes Hospital in Gaza's North and Captures Key Part of South

No one was killed but the attack hit the Ahli Arab Hospital, a mainstay of Gaza's decimated health care system. Separately, Israel said its troops had expanded their occupation of southern Gaza.

MOTIVATION, CONT.

MOTIVATION, CONT.

Karl Hansen @karl_fh · 2h

Israelis have "children", while Palestinians have "people aged 18 and younger".

> The hostages to be freed are women and children, and the Palestinian prisoners are also women and people aged 18 and younger, both sides have confirmed.

Guardian news @guardianne... · 14h

Israel-Hamas ceasefire and hostage deal won't happen before Friday, Israeli and US officials say dlvr.it/SzBx77

MOTIVATION, CONT.

MOTIVATION, CONT.

MOTIVATION, CONT.

MOTIVATION, CONT.

MOTIVATION, CONT.

MOTIVATION, CONT.

MEDIA FRAMING CHOICES IN CONFLICT

- News outlets have wide latitude in how to frame conflicts, with important implications for the mass attitudes

MEDIA FRAMING CHOICES IN CONFLICT

- News outlets have wide latitude in how to frame conflicts, with important implications for the mass attitudes
- Especially true in Gaza

MEDIA FRAMING CHOICES IN CONFLICT

- News outlets have wide latitude in how to frame conflicts, with important implications for the mass attitudes
- Especially true in Gaza
  - A conflict with extensive Western coverage, but with little on-the-ground reporting

MEDIA FRAMING CHOICES IN CONFLICT

- News outlets have wide latitude in how to frame conflicts, with important implications for the mass attitudes
- Especially true in Gaza
  - A conflict with extensive Western coverage, but with little on-the-ground reporting
  - A very polarizing issue that might trigger different editorial processes

MEDIA FRAMING CHOICES IN CONFLICT

- News outlets have wide latitude in how to frame conflicts, with important implications for the mass attitudes
- Especially true in Gaza
  - A conflict with extensive Western coverage, but with little on-the-ground reporting
  - A very polarizing issue that might trigger different editorial processes
- War reporting is unique: taking empathy to the extreme, human-centered frames may dishearten and demobilize

How do news organizations describe violent
(and polarizing) conflicts abroad?

How do news organizations describe violent (and polarizing) conflicts abroad?

How do these editorial choices influence media consumption and public attitudes toward the conflict and its victims?

How do news organizations describe violent (and polarizing) conflicts abroad?

How do these editorial choices influence media consumption and public attitudes toward the conflict and its victims?

When does humanizing coverage change attitudes about foreign conflict?

How do news organizations describe violent (and polarizing) conflicts abroad?

How do these editorial choices influence media consumption and public attitudes toward the conflict and its victims?

When does humanizing coverage change attitudes about foreign conflict?

ORIGINAL PLAN
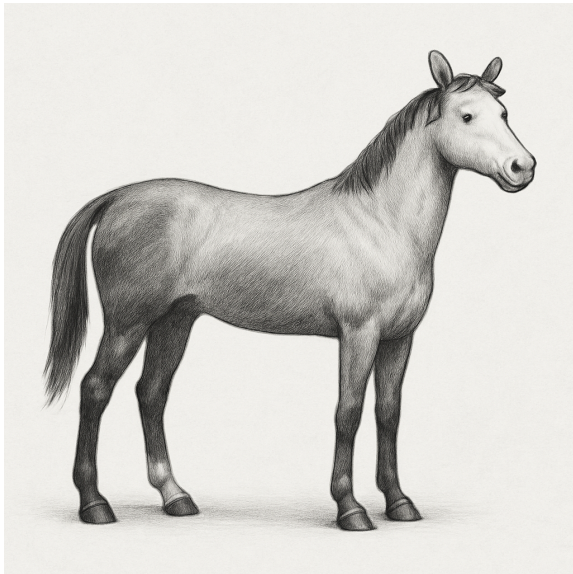
ORIGINAL PLAN

Quantitative Content Analysis

ORIGINAL PLAN

Quantitative Content Analysis

- Scrape and clean ~42,000 articles about the Israel-Hamas war from 19 international outlets, October 2023-September 2024

ORIGINAL PLAN

Quantitative Content Analysis

- Scrape and clean ~42,000 articles about the Israel-Hamas war from 19 international outlets, October 2023-September 2024
- Tagging and classification

ORIGINAL PLAN

Quantitative Content Analysis

- Scrape and clean ~42,000 articles about the Israel-Hamas war from 19 international outlets, October 2023-September 2024

- Tagging and classification

  1 Classify texts/articles according to target group using an open-source LLM

ORIGINAL PLAN

Quantitative Content Analysis

- Scrape and clean ~42,000 articles about the Israel-Hamas war from 19 international outlets, October 2023-September 2024
- Tagging and classification
  1. Classify texts/articles according to target group using an open-source LLM
  2. Record frames present in articles using an open-source LLM

ORIGINAL PLAN

Quantitative Content Analysis

- Scrape and clean ~42,000 articles about the Israel-Hamas war from 19 international outlets, October 2023-September 2024

- Tagging and classification

    1 Classify texts/articles according to target group using an open-source LLM

    2 Record frames present in articles using an open-source LLM
    3 Identify visual elements of relevant frames in top images of articles using visual transformers and LVMs

ORIGINAL PLAN

Quantitative Content Analysis

- Scrape and clean ~42,000 articles about the Israel-Hamas war from 19 international outlets, October 2023-September 2024

- Tagging and classification

  1 Classify texts/articles according to target group using an open-source LLM

  2 Record frames present in articles using an open-source LLM

  3 Identify visual elements of relevant frames in top images of articles using visual transformers and LVMs

- Analysis and comparison between groups

ORIGINAL PLAN

Quantitative Content Analysis

- Scrape and clean ~42,000 articles about the Israel-Hamas war from 19 international outlets, October 2023-September 2024

- Tagging and classification

  1 Classify texts/articles according to target group using an open-source LLM

  2 Record frames present in articles using an open-source LLM
  3 Identify visual elements of relevant frames in top images of articles using visual transformers and LVMs

- Analysis and comparison between groups

  1 Comparison of the prevalence of verbal and visual frames between groups

ORIGINAL PLAN

Quantitative Content Analysis

- Scrape and clean ~42,000 articles about the Israel-Hamas war from 19 international outlets, October 2023-September 2024

- Tagging and classification

  1 Classify texts/articles according to target group using an open-source LLM

  2 Record frames present in articles using an open-source LLM

  3 Identify visual elements of relevant frames in top images of articles using visual transformers and LVMs

- Analysis and comparison between groups

  1 Comparison of the prevalence of verbal and visual frames between groups

  2 Identification of predictive embeddings of frames-target groups (SHAP values and Interpretable ML tools)

ORIGINAL PLAN

Quantitative Content Analysis

- Scrape and clean ~42,000 articles about the Israel-Hamas war from 19 international outlets, October 2023-September 2024

- Tagging and classification

  1 Classify texts/articles according to target group using an open-source LLM

  2 Record frames present in articles using an open-source LLM

  3 Identify visual elements of relevant frames in top images of articles using visual transformers and LVMs

- Analysis and comparison between groups

  1 Comparison of the prevalence of verbal and visual frames between groups

  2 Identification of predictive embeddings of frames-target groups (SHAP values and Interpretable ML tools)

  3 Semantic dissection: semantic role labeling and syntax analysis to capture blame, accountability, and framing → use of passive vs. active voice, obfuscation of subject of sentence, use of numbers, casting doubt, sources cited, etc.

ORIGINAL PLAN

Quantitative Content Analysis

- Scrape and clean ~42,000 articles about the Israel-Hamas war from 19 international outlets, October 2023-September 2024 (✓*)

- Tagging and classification

  ❶ Classify texts/articles according to target group using an open-source LLM (✗)
  ❷ Record frames present in articles using an open-source LLM (✗)
  ❸ Identify visual elements of relevant frames in top images of articles using visual transformers and LVMs (±)

- Analysis and comparison between groups

  ❶ Comparison of the prevalence of verbal and visual frames between groups (±)
  ❷ Identification of predictive embeddings of frames-target groups (SHAP values and Interpretable ML tools) (✗)
  ❸ Semantic dissection: semantic role labeling and syntax analysis to capture blame, accountability, and framing → use of passive vs. active voice, obfuscation of subject of sentence, use of numbers, casting doubt, sources cited, etc. (in progress)

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs
- Developed a codebook for tagging and classification

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs
- Developed a codebook for tagging and classification
  - Target: Israel(i), Palestine(ian), Both, None

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs
- Developed a codebook for tagging and classification
  - Target: Israel(i), Palestine(ian), Both, None
  - Frames: General harm, Civilian, Harm against people, Harm infrastructure, Blame, Events in other countries

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs
- Developed a codebook for tagging and classification
  - Target: Israel(i), Palestine(ian), Both, None
  - Frames: General harm, Civilian, Harm against people, Harm infrastructure, Blame, Events in other countries
  - Multiple iterations: authors and undergraduate research assistants

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs
- Developed a codebook for tagging and classification
    - Target: Israel(i), Palestine(ian), Both, None
    - Frames: General harm, Civilian, Harm against people, Harm infrastructure, Blame, Events in other countries
    - Multiple iterations: authors and undergraduate research assistants
    - Includes descriptions, positive and negative examples, and clarifications/notes

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs
- Developed a codebook for tagging and classification
  - Target: Israel(i), Palestine(ian), Both, None
  - Frames: General harm, Civilian, Harm against people, Harm infrastructure, Blame, Events in other countries
  - Multiple iterations: authors and undergraduate research assistants
  - Includes descriptions, positive and negative examples, and clarifications/notes
  - As factual as possible

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs
- Developed a codebook for tagging and classification
    - Target: Israel(i), Palestine(ian), Both, None
    - Frames: General harm, Civilian, Harm against people, Harm infrastructure, Blame, Events in other countries
    - Multiple iterations: authors and undergraduate research assistants
    - Includes descriptions, positive and negative examples, and clarifications/notes
    - As factual as possible
- Strategies:

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs
- Developed a codebook for tagging and classification
  - Target: Israel(i), Palestine(ian), Both, None
  - Frames: General harm, Civilian, Harm against people, Harm infrastructure, Blame, Events in other countries
  - Multiple iterations: authors and undergraduate research assistants
  - Includes descriptions, positive and negative examples, and clarifications/notes
  - As factual as possible
- Strategies:
  - Use codebook to prompt Mistral 7B

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs
- Developed a codebook for tagging and classification
  - Target: Israel(i), Palestine(ian), Both, None
  - Frames: General harm, Civilian, Harm against people, Harm infrastructure, Blame, Events in other countries
  - Multiple iterations: authors and undergraduate research assistants
  - Includes descriptions, positive and negative examples, and clarifications/notes
  - As factual as possible
- Strategies:
  - Use codebook to prompt Mistral 7B
  - Use training sample ($n = 1,000$) to tune BERT Classifier and Mistral

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs
- Developed a codebook for tagging and classification
  - Target: Israel(i), Palestine(ian), Both, None
  - Frames: General harm, Civilian, Harm against people, Harm infrastructure, Blame, Events in other countries
  - Multiple iterations: authors and undergraduate research assistants
  - Includes descriptions, positive and negative examples, and clarifications/notes
  - As factual as possible
- Strategies:
  - Use codebook to prompt Mistral 7B
  - Use training sample ($n = 1,000$) to tune BERT Classifier and Mistral
  - Use codebook to prompt ChatGPT

CHALLENGES: IDENTIFYING TARGET GROUPS AND FRAMES

- Switched from article level to 5-sentences paragraphs
- Developed a codebook for tagging and classification
  - Target: Israel(i), Palestine(ian), Both, None
  - Frames: General harm, Civilian, Harm against people, Harm infrastructure, Blame, Events in other countries
  - Multiple iterations: authors and undergraduate research assistants
  - Includes descriptions, positive and negative examples, and clarifications/notes
  - As factual as possible
- Strategies:
  - Use codebook to prompt Mistral 7B
  - Use training sample ($n = 1,000$) to tune BERT Classifier and Mistral
  - Use codebook to prompt ChatGPT
- Results: Weak performance with all three, with ChatGPT being the best (but still not great)

INTER-CODER RELIABILITY

Inter−Coder Kappa Heatmap
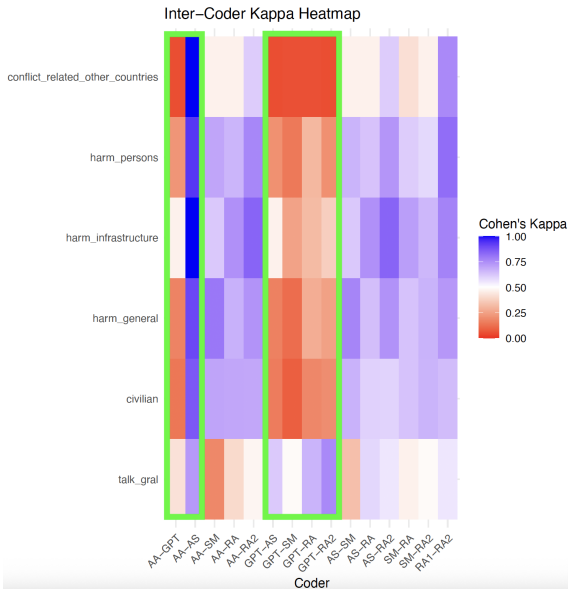
RELIABILITY COEFFICIENTS (MODIFIED PROMPT)

RELIABILITY COEFFICIENTS (MODIFIED PROMPT)

- Reliance on "buzzwords": Palestine, Israel, son, terrorist

Reliability coefficients and interpretation
(Civilian)

Metric	Value	Interpretation
Percent Agreement	61.5%	Fair
Cohen's Kappa	0.388	Fair
Weighted Kappa	0.513	Fair
Scott's Pi	0.383	Fair
Krippendorff's Alpha	0.383	Fair

RELIABILITY COEFFICIENTS (MODIFIED PROMPT)

- Reliance on "buzzwords": Palestine, Israel, son, terrorist
- Human coders: context and interdependence of categories

Reliability coefficients and interpretation
(Civilian)

Metric	Value	Interpretation
Percent Agreement	61.5%	Fair
Cohen's Kappa	0.388	Fair
Weighted Kappa	0.513	Fair
Scott's Pi	0.383	Fair
Krippendorff's Alpha	0.383	Fair

RELIABILITY COEFFICIENTS (MODIFIED PROMPT)

- Reliance on "buzzwords": Palestine, Israel, son, terrorist
- Human coders: context and interdependence of categories
- Hard cases: e.g. "hostage"= harm?

Reliability coefficients and interpretation
(Civilian)

Metric	Value	Interpretation
Percent Agreement	61.5%	Fair
Cohen's Kappa	0.388	Fair
Weighted Kappa	0.513	Fair
Scott's Pi	0.383	Fair
Krippendorff's Alpha	0.383	Fair

CHALLENGES: THE QUANTITY OF INTEREST

- Differences in frames per group: how do we understand them?

CHALLENGES: THE QUANTITY OF INTEREST

- Differences in frames per group: how do we understand them?
- Our preliminary quantitative and anecdotal results:

CHALLENGES: THE QUANTITY OF INTEREST

- Differences in frames per group: how do we understand them?
- Our preliminary quantitative and anecdotal results:
  - Differences in mentions of civilians, harm, and other relevant dimensions

CHALLENGES: THE QUANTITY OF INTEREST

- Differences in frames per group: how do we understand them?
- Our preliminary quantitative and anecdotal results:
  - Differences in mentions of civilians, harm, and other relevant dimensions
  - No sharp differences in other areas

CHALLENGES: THE QUANTITY OF INTEREST

- Differences in frames per group: how do we understand them?
- Our preliminary quantitative and anecdotal results:
    - Differences in mentions of civilians, harm, and other relevant dimensions
    - No sharp differences in other areas
    - How do we contextualize these findings? Reflection of reality or a framing strategy?

WHAT WE DID
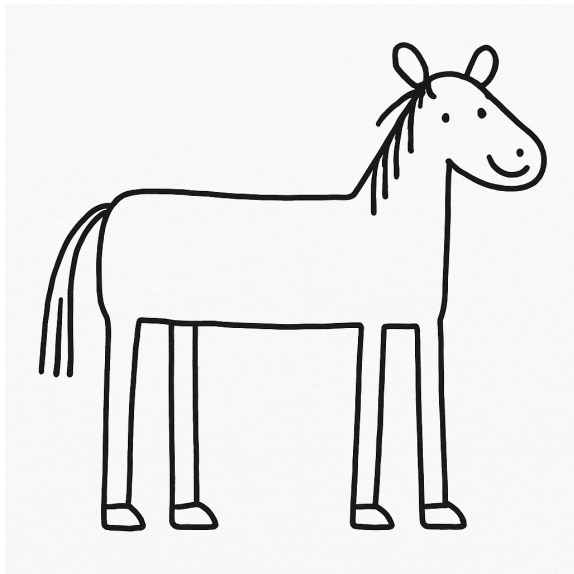
WHAT WE DID: IDENTIFICATION OF FRAMES

- Create dictionaries for each of our frames: Human-centered →
  Harm, Civilian; Geopolitical → Government actors, Blame;
  Hostages and Prisoners*

WHAT WE DID: IDENTIFICATION OF FRAMES

- Create dictionaries for each of our frames: Human-centered → Harm, Civilian; Geopolitical → Government actors, Blame; Hostages and Prisoners*
  - Set seed words for each

WHAT WE DID: IDENTIFICATION OF FRAMES

- Create dictionaries for each of our frames: Human-centered →
  Harm, Civilian; Geopolitical → Government actors, Blame;
  Hostages and Prisoners*
    - Set seed words for each
    - Use sentence transformer (MiniLM-L6) to identify closest
      embeddings to seed words

WHAT WE DID: IDENTIFICATION OF FRAMES

- Create dictionaries for each of our frames: Human-centered →
  Harm, Civilian; Geopolitical → Government actors, Blame;
  Hostages and Prisoners*
  - Set seed words for each
  - Use sentence transformer (MiniLM-L6) to identify closest
    embeddings to seed words
  - Use cosine similarity to map embeddings in our data to the
    embeddings above

WHAT WE DID: IDENTIFICATION OF FRAMES

- Create dictionaries for each of our frames: Human-centered →
  Harm, Civilian; Geopolitical → Government actors, Blame;
  Hostages and Prisoners*
    - Set seed words for each
    - Use sentence transformer (MiniLM-L6) to identify closest
      embeddings to seed words
    - Use cosine similarity to map embeddings in our data to the
      embeddings above
    - Choose "most representative words" per dimension

WHAT WE DID: IDENTIFICATION OF FRAMES

- Create dictionaries for each of our frames: Human-centered →
  Harm, Civilian; Geopolitical → Government actors, Blame;
  Hostages and Prisoners*
    - Set seed words for each
    - Use sentence transformer (`MiniLM-L6`) to identify closest
      embeddings to seed words
    - Use cosine similarity to map embeddings in our data to the
      embeddings above
    - Choose "most representative words" per dimension
    - Manual curation of seed words lists

WHAT WE DID: IDENTIFICATION OF FRAMES

- Create dictionaries for each of our frames: Human-centered →
  Harm, Civilian; Geopolitical → Government actors, Blame;
  Hostages and Prisoners*
  - Set seed words for each
  - Use sentence transformer (MiniLM-L6) to identify closest
    embeddings to seed words
  - Use cosine similarity to map embeddings in our data to the
    embeddings above
  - Choose "most representative words" per dimension
  - Manual curation of seed words lists
- Compute the prevalence of the words in each dictionary in each
  text (after removing stop words)

WHAT WE DID: IDENTIFICATION OF FRAMES

- Create dictionaries for each of our frames: Human-centered →
  Harm, Civilian; Geopolitical → Government actors, Blame;
  Hostages and Prisoners*
    - Set seed words for each
    - Use sentence transformer (MiniLM-L6) to identify closest
      embeddings to seed words
    - Use cosine similarity to map embeddings in our data to the
      embeddings above
    - Choose "most representative words" per dimension
    - Manual curation of seed words lists
- Compute the prevalence of the words in each dictionary in each
  text (after removing stop words)
- Similar amount of keywords per dimension

RESULTS: PREVALENCE OF FRAMES IN FULL CORPUS

Mean Proportion of Words by Dimension in Total Corpus
(Conflict=Israel–Palestine)
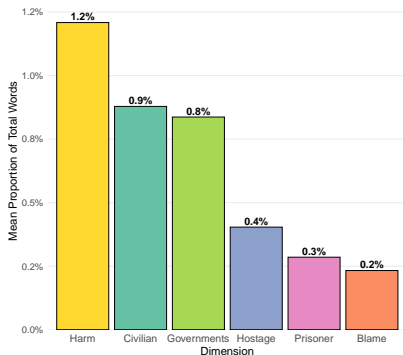
RESULTS: PREVALENCE OF FRAMES IN FULL CORPUS

Mean Proportion of Words by Dimension in Total Corpus
(Conflict=Israel–Palestine)
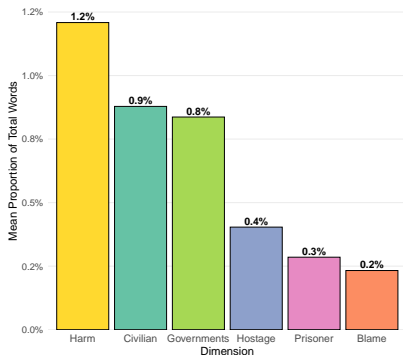
Media Coverage Dimensions by Outlet
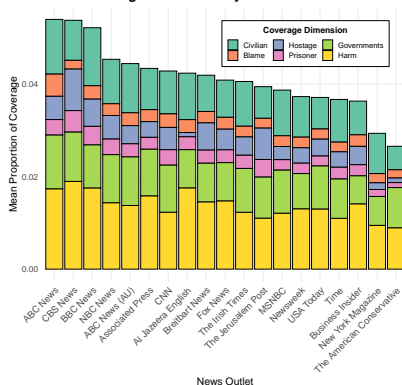
WHAT WE DID: IDENTIFICATION OF TARGETS

- Stratified random sample of 4,500 articles = 22,496 5-sentence paragraphs

WHAT WE DID: IDENTIFICATION OF TARGETS

- Stratified random sample of 4,500 articles = 22,496 5-sentence paragraphs
- Prompted ChatGPT (modified and simplified prompt) to answer whether the text talks about: 1) civilians belonging to Palestine? 2) civilians belonging to Israel? 3) harm done against Palestine or Palestinians? and 4) harm done against Israel or Israelis?

WHAT WE DID: IDENTIFICATION OF TARGETS

- Stratified random sample of 4,500 articles = 22,496 5-sentence paragraphs
- Prompted ChatGPT (modified and simplified prompt) to answer whether the text talks about: 1) civilians belonging to Palestine? 2) civilians belonging to Israel? 3) harm done against Palestine or Palestinians? and 4) harm done against Israel or Israelis?
- Filter *only* Israel or *only* Palestine → 8,624 paragraphs in ~ 3,400 articles

WHAT WE DID: IDENTIFICATION OF TARGETS

- Stratified random sample of 4,500 articles = 22,496 5-sentence paragraphs
- Prompted ChatGPT (modified and simplified prompt) to answer whether the text talks about: 1) civilians belonging to Palestine? 2) civilians belonging to Israel? 3) harm done against Palestine or Palestinians? and 4) harm done against Israel or Israelis?
- Filter *only* Israel or *only* Palestine → 8,624 paragraphs in ~ 3,400 articles
- We repeated this exercise with a small hand-coded sample (~600 paragraphs): results are stronger

RESULTS: PREVALENCE OF FRAMES BY GROUP

Proportion of Words by Dimension and Group
(Conflict=Israel–Palestine)

Target group in text   Israel   Palestine
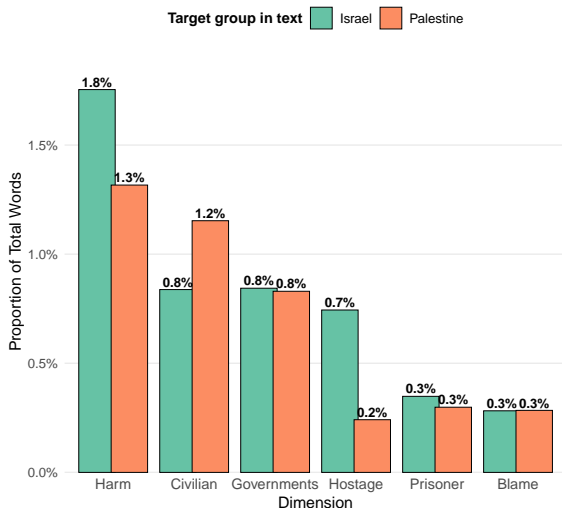
WHAT WE DID: "REALITY" BENCHMARK

- Use data on civilian and military casualties from ACLED

WHAT WE DID: "REALITY" BENCHMARK

- Use data on civilian and military casualties from ACLED
- Visualize trends over time for both groups: casualties AND prevalence of Harm & Civilian frames

WHAT WE DID: "REALITY" BENCHMARK

- Use data on civilian and military casualties from ACLED
- Visualize trends over time for both groups: casualties AND prevalence of Harm & Civilian frames
- Compute ratios of "civilian-related language" and "harm-related language," and ratios of casualties for the two groups:

WHAT WE DID: "REALITY" BENCHMARK

- Use data on civilian and military casualties from ACLED
- Visualize trends over time for both groups: casualties AND prevalence of Harm & Civilian frames
- Compute ratios of "civilian-related language" and "harm-related language," and ratios of casualties for the two groups:
    - For outlet k in day t: Proportion of paragraphs related to Palestinian Civilians/Proportion of paragraphs related to Israeli Civilians

WHAT WE DID: "REALITY" BENCHMARK

- Use data on civilian and military casualties from ACLED
- Visualize trends over time for both groups: casualties AND prevalence of Harm & Civilian frames
- Compute ratios of "civilian-related language" and "harm-related language," and ratios of casualties for the two groups:
  - For outlet k in day t: Proportion of paragraphs related to Palestinian Civilians/Proportion of paragraphs related to Israeli Civilians
  - For outlet k in day t: Proportion of paragraphs related to Harm against Palestinian/Proportion of paragraphs related Harm against Israeli Civilians

WHAT WE DID: "REALITY" BENCHMARK

- Use data on civilian and military casualties from ACLED
- Visualize trends over time for both groups: casualties AND prevalence of Harm & Civilian frames
- Compute ratios of "civilian-related language" and "harm-related language," and ratios of casualties for the two groups:
  - For outlet k in day t: Proportion of paragraphs related to Palestinian Civilians/Proportion of paragraphs related to Israeli Civilians
  - For outlet k in day t: Proportion of paragraphs related to Harm against Palestinian/Proportion of paragraphs related Harm against Israeli Civilians
  - Casualties in day t: Palestinian (civilian) fatalities/Israeli (civilian) fatalities

WHAT WE DID: "REALITY" BENCHMARK

- Use data on civilian and military casualties from ACLED
- Visualize trends over time for both groups: casualties AND prevalence of Harm & Civilian frames
- Compute ratios of "civilian-related language" and "harm-related language," and ratios of casualties for the two groups:
    - For outlet k in day t: Proportion of paragraphs related to Palestinian Civilians/Proportion of paragraphs related to Israeli Civilians
    - For outlet k in day t: Proportion of paragraphs related to Harm against Palestinian/Proportion of paragraphs related Harm against Israeli Civilians
    - Casualties in day t: Palestinian (civilian) fatalities/Israeli (civilian) fatalities
- Expectation: correspondence of ratios.

RESULTS: FRAMING AND FATALITIES

Coverage of civilians over time and civilian fatalities
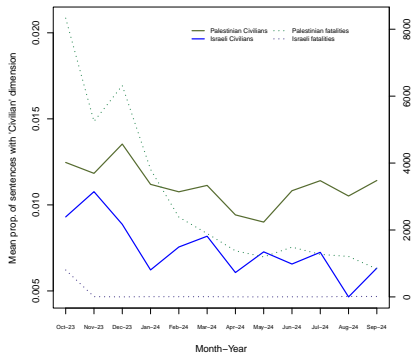
RESULTS: FRAMING AND FATALITIES

Coverage of civilians over time and civilian fatalities
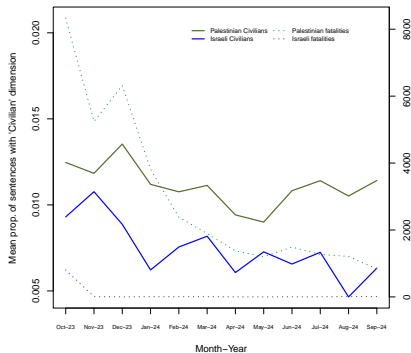
Coverage of harm over time and total fatalities
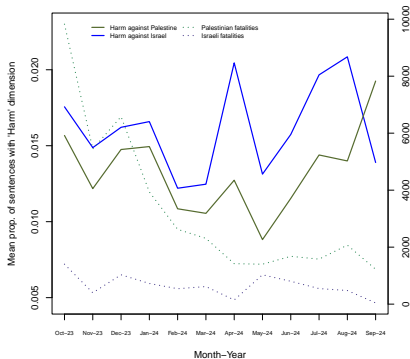
RESULTS: FRAMING AND FATALITIES, CONT.
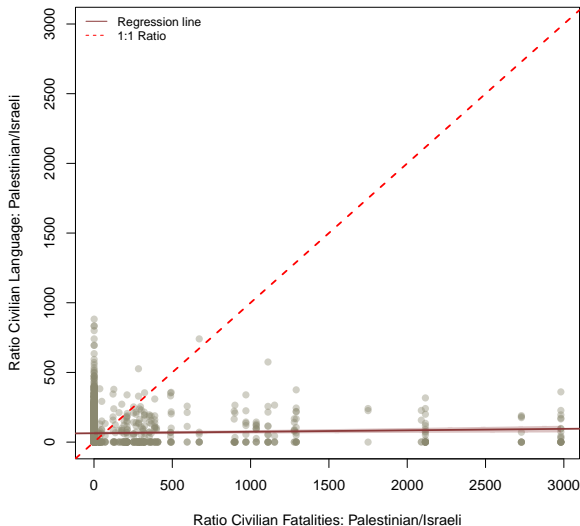
OTHER THINGS THAT WE HAVE TRIED AND ARE TRYING

- Comparisons to the Ukraine-Russia war

OTHER THINGS THAT WE HAVE TRIED AND ARE TRYING

- Comparisons to the Ukraine-Russia war
- Masking places and "buzzwords" to detect meaningful differences in language

OTHER THINGS THAT WE HAVE TRIED AND ARE TRYING

- Comparisons to the Ukraine-Russia war
- Masking places and "buzzwords" to detect meaningful differences in language
- Prompt engineering

OTHER THINGS THAT WE HAVE TRIED AND ARE TRYING

- Comparisons to the Ukraine-Russia war
- Masking places and "buzzwords" to detect meaningful differences in language
- Prompt engineering
- Build a larger and more balanced training sample

OTHER THINGS THAT WE HAVE TRIED AND ARE TRYING

- Comparisons to the Ukraine-Russia war
- Masking places and "buzzwords" to detect meaningful differences in language
- Prompt engineering
- Build a larger and more balanced training sample
- Analysis of images using LLaVA and HuggingFaces Face Analyzer

OTHER THINGS THAT WE HAVE TRIED AND ARE TRYING

- Comparisons to the Ukraine-Russia war
- Masking places and "buzzwords" to detect meaningful differences in language
- Prompt engineering
- Build a larger and more balanced training sample
- Analysis of images using LLaVA and HuggingFaces Face Analyzer
- Semantic analysis

OTHER THINGS THAT WE HAVE TRIED AND ARE TRYING

- Comparisons to the Ukraine-Russia war
- Masking places and "buzzwords" to detect meaningful differences in language
- Prompt engineering
- Build a larger and more balanced training sample
- Analysis of images using LLaVA and HuggingFaces Face Analyzer
- Semantic analysis
- Complement data with other important sources like NYT, WaPo, and The Guardian

OTHER THINGS THAT WE HAVE TRIED AND ARE TRYING

- Comparisons to the Ukraine-Russia war
- Masking places and "buzzwords" to detect meaningful differences in language
- Prompt engineering
- Build a larger and more balanced training sample
- Analysis of images using LLaVA and HuggingFaces Face Analyzer
- Semantic analysis
- Complement data with other important sources like NYT, WaPo, and The Guardian
- Experiment testing humanizing frames on attitudes and mobilization

Thank you!

Questions/feedback: smtorres@ucla.edu

APPENDIX

INDEX

- Theoretical Framework

- Content analysis
    - Data collection
    - News outlets included
    - Classification workflow
    - War words
    - Data on Casualties
    - Comparison with Ukraine and Russia

- Survey Experiment
    - Survey overview
    - Goals
    - Preference-Incorporating Choice and Assignment: Motivation and Procedure
    - Example
    - Forced choice
    - Outcomes: Outgroup attitudes , Policy views , Emotions & Mobilization

DESCRIBING MEDIA FRAMES

- News outlets highlight some aspects of events while omitting others (Druckman, 2004)

- "Human-centered frames" trigger strong emotions and moral outrage – potentially at the expense of broader context (Iyengar, 1991; Kampf and Liebes, 2013)

- Sympathetic portrayals more likely for white, Western victims (Myers, Klak and Koehl, 1996)

- We estimate prevalence of human-centered frames of Palestinians and Israelis in the the Gaza conflict

Table index

EFFECTS OF MEDIA FRAMES

How does human-centered framing influence news consumption and attitudes?

- Coverage incongruent w/ prior views → cognitive dissonance → avoidance (Stroud, 2008)
- Coverage congruent w/ prior views → helplessness → avoidance (Slovic, 2007; Eisenberg et al., 1989; Cameron and Payne, 2011)
- Among uncommitted people, human-centered frames may be especially effective in shifting attitudes

DATA COLLECTION

1. Query the `NewsAPI` to obtain the list of articles of 19 news outlets (outlets) using the search terms: "Gaza", "Palestine", "Palestinian", and "Israel" (separated by OR) $\rightarrow n = 47,375 articles$

2. Collect title, source, date of publication, author, description, URL of the top image, and URL of main article.

3. Scrape from each link the main text and images (using `newspaper3k`) $\rightarrow n = 42,055 articles$ (losses due to pay walls and faulty URLs)

4. Clean-up the text: remove ad-related content, slogans, social media accounts, symbols, etc. $\rightarrow$ Still not perfect

Table index

NEWS OUTLETS INCLUDED

- ABC News
- ABC News Australia
- Al Jazeera (English)
- Associated Press
- BBC News
- Breitbart News
- Business Insider
- CBS News
- CNN
- Fox News

- MSNBC
- NBC News
- New York Magazine
- Newsweek
- The American Conservative
- The Irish Times
- The Jerusalem Post
- Time
- USA Today

Number of articles in corpus by outlet

Table index
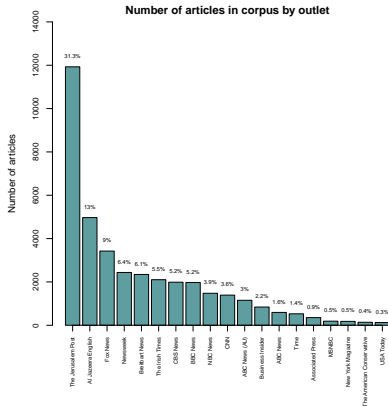
CLASSIFICATION WORKFLOW

- Collect news articles
- Dictionary of "war" terms to detect articles related to the actual conflict and not adjacent events (e.g. protests or foreign policy of other nations)
  $\rightarrow$ Keep only those related to war $n = 38,146$ articles
- Split the articles into 5-sentence paragraphs/chunks of text (sentence defined by period or line break)
- Determine the target of each paragraph
- Determine whether each of the frames of interest are present in the text

Table index

WORDS RELATED TO WAR

Positive

war	conflict	invasion	attack	military	combat	battle
strike	bomb	missile	troops	forces	army	navy
airforce	soldier	fighting	violence	aggression	assault	Palestine
raid	siege	occupation	border clash	skirmish	hostilities	offensive
hostages	hostage	invasion	Israel	Gaza		

Negative

protest	statement	campus	actress	sport	actor
summit	cultural exchange	economic	scientific	entertainment	

Table index

CODEBOOK: TALK GENERAL

Mark the column based on whether the paragraph includes any mention of Israelis or Palestinians in general. This encompasses all references to Israelis or Israel, Palestinians or Palestine occurring inside Israel or Palestine, including general mentions, militant groups (e.g., IDF, Hamas), the word "terrorist," government bodies (e.g., the Israeli Government, the PLO), government actions, and civilians. Also includes any groups generally associated with Israel within the region (Israel and Palestine).

Notes: Do not mark if the paragraph only mentions groups or organizations abroad; such mentions should be coded in conflict_related_other_countries. If any Israeli-specific or Palestinian-specific columns are marked (1, 2, or 3), then this column should also be marked (unless the paragraph is solely about events abroad or complex minority populations). Mark '0' if there is no mention of Israelis, Israel, Palestine, or Palestinians as per the above criteria.

CODEBOOK: CIVILIAN

Mark if the paragraph specifically mentions civilians-non-military, non-government individuals-who are Israeli, Palestinian, or both, including their lives, experiences, or victimization.

Example:

- 0: "The attack targeted military installations."
- 1: "Palestinian civilians in Gaza are suffering due to the blockade."
- 2: "Israeli civilians were injured in the rocket strike."
- 3: "The conflict has caused immense suffering for both Palestinian and Israeli civilians."

Notes: Include references to civilians killed, injured, displaced, hostages, prisoners, refugees, or displaced persons. Soldiers described using civilian language (e.g., "kids," "sons," "daughters") should also be coded here.

CODEBOOK: HARM GENERAL

Mark if the paragraph mentions harm, suffering, or negative conse-
quences experienced by Israelis, Palestinians, or both (physical, psy-
chological, property destruction, displacement, hardships, etc.

Example:

- 0: "There were no reports of casualties or damage."
- 1: "Palestinians face water shortages due to damaged infrastructure in Gaza."
- 2: "Psychological trauma from repeated rocket attacks has left many Israelis unable to sleep."
- 3: "Both Israeli and Palestinian communities are grieving after the recent escalation."

Notes: Include current, historical, or potential harm. Mentions of harm
without specifying a perpetrator should still be coded. If
harm_infrastructure or harm_persons is not zero, then this column
should also not be zero. Harm does not need to originate from the
Israeli-Palestinian conflict itself.

CODEBOOK: HARM – INFRASTRUCTURE

> Mark if the paragraph mentions harm, destruction, or damage to property or infrastructure affecting Israelis, Palestinians, or both.

Example:

- 0: "The airstrike hit an open field without damaging any buildings."
- 1: "The water treatment plant in Gaza was destroyed."
- 2: "Israeli schools were damaged by rocket attack."
- 3: "Homes on both sides were destroyed during the crossfire."

CODEBOOK: HARM – PEOPLE

Mark if the paragraph mentions harm, injury, or suffering of specific individuals or groups (Israeli, Palestinian, or both).

Example:
- 0: "No casualties were reported, and all individuals were unharmed."
- 1: "Dozens of Palestinians were injured during the raid."
- 2: "Israeli children are traumatized by constant air sirens."
- 3: "Both Palestinians and Israelis are suffering from psychological effects of the violence."

Notes: Includes displacement, trauma, genocide references, or any suffering. Harm can be caused by external actors.

CODEBOOK: BLAME ATTRIBUTION

Mark if the paragraph attributes responsibility for harm, suffering, or negative consequences to Israelis, Palestinians, or both.

Example:

- 0: "Civilians on both sides continue to suffer." (No blame assigned)
- 1: "Palestinian militants launched an attack on Israeli settlements."
- 2: "Israeli airstrikes caused widespread destruction in Gaza."
- 3: "Both Israel and Hamas have been accused of war crimes."

Notes: Include explicit or implicit blame (e.g., "The blockade has worsened the crisis" implies blame). Do not mark if harm is described without assigning responsibility.

CODEBOOK: CONFLICT RELATED TO OTHER COUNTRIES

> Mark '1' if the paragraph discusses events related to the Israeli-Palestinian conflict occurring outside Israel/Palestine. This includes protests, incidents abroad, foreign leaders' statements, foreign nationals affected, etc.

Example:

- 1: "Pro-Palestinian protestors gathered in London."
- 1: "The U.S. Secretary of State called for a ceasefire."
- 1: "Anti-Semitic incidents increased in Europe."
- 1 & Other Columns: "A French diplomat described destruction in Gaza as unacceptable." (harm_general may also apply)

Notes: This column is not mutually exclusive. If the paragraph only discusses events abroad unrelated to Israelis/Palestinians in the region, mark only this column '1' and others '0'. Otherwise, mark additional relevant columns.

DATA ON CASUALTIES AND CIVILIAN FATALITIES

- Data from the Armed Conflict Location and Event Data Project (ACLED)
- ACLED provides granular, event-level data on attacks – including airstrikes, shelling, and armed clashes – and associated fatalities, disaggregated by date and type of target: Israeli, Palestinian, or Other, as well as Authorities/Government/Combatant or Civilians
- Data compiled from a wide range of local and international news sources, humanitarian reports, and partner organizations
- It includes data from the Ministry of Health of Gaza
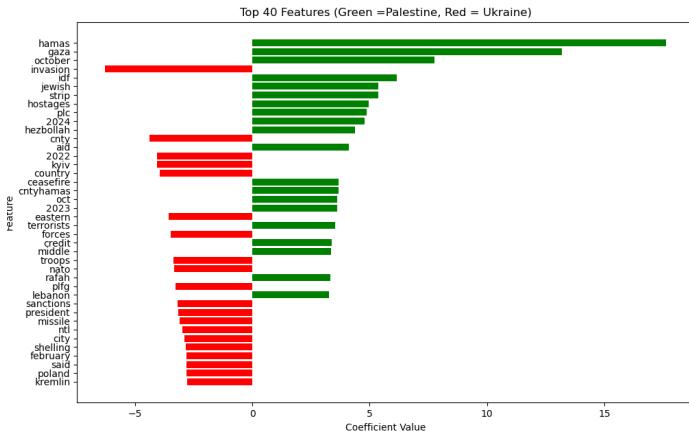
Table index

COMPARISON ISRAEL/PALESTINE VS. RUSSIA/UKRAINE

- Masked cities, areas, countries, and top leaders
- Embedding analysis: Mapping of UMAP and TSNE Components, Top Features

Document Embeddings Visualization using TSNE

Table index

COMPARISON ISRAEL/PALESTINE VS. RUSSIA/UKRAINE, CONT.

Top 40 Features (Green = Palestine, Red = Ukraine)

Table index

SURVEY OVERVIEW

- Goal: Examine how media framing choices of the Gaza war influence news consumption and subsequent attitudes
- Does humanizing coverage trigger avoidance? Among whom?
  - Can affirmations of ingroup suffering mitigate the effects of cognitive dissonance on avoidance?
  - Can empowering calls to action mitigate the effects of emotional exhaustion on avoidance?
- What is the effect of news coverage on attitudes, emotions, and mobilization?

Table index

ORIGINAL AND MODIFIED PLAN: SURVEY EXPERIMENT

Survey Experiment

- Survey experiment on U.S. public randomizing exposure to real-world news about the Gaza conflict
- Treatment: humanizing vs. de-humanizing frames (✗)
- Hypothesize that humanizing coverage:
  - Triggers avoidance both for extreme sympathizers and extreme opponents
  - Most persuasive among 'neutrals', relative to geopolitical or infrastructure frames

PREFERENCE-INCORPORATING CHOICE AND ASSIGNMENT DESIGN

- Design: Preference-Incorporating Choice and Assignment
  (Benedictis-Kessner et al., 2019)

- Combines self-selection and random assignment to estimate causal effects of news exposure while accounting for avoidance

Table index

PREFERENCE-INCORPORATING CHOICE AND ASSIGNMENT DESIGN, CONT.

1 Pre-treatment measure of sympathy toward Israelis/Palestinians

2 Headline task: Present three headlines with randomly assigned valence (favorable toward Palestinians vs. Israelis) and framing style
  - Human-centered frame
  - Geopolitical frame
  - Placebo headline

3 Ask respondents which story they would like to read

4 Randomly assign half of respondents to read self-selected story and other half to read one of the others, chosen randomly

5 Measure policy attitudes, empathy, emotions, and mobilization

Table index

EXAMPLE HEADLINE TASK

Please read the headlines of three news articles below. Which would you be most interested in reading?

- Dozens shot dead and injured near Gaza aid hub, health ministry and doctors say
- Hamas pushes back on the latest Gaza ceasefire proposal offered by the U.S.
- Heat waves are getting more dangerous with climate change – and we may still be underestimating them

Hypotheses

1. (Avoidance of incongruent articles) Respondents are less likely to select headlines that are incongruent with pre-existing sympathies

2. (Avoidance of humanizing articles) For those with strong prior sympathies, headlines highlighting suffering are especially likely to trigger avoidance
   - Congruent coverage: sympathy fatigue
   - Incongruent coverage: cognitive dissonance

FORCED EXPOSURE

To measure effects of consuming media while accounting for selection bias, we then randomize the articles respondents are asked to read

Enables estimation of:

- Observational differences between those who self-select different articles
- Treatment effects by strata of article selection and prior sympathy

Table index

OUTGROUP ATTITUDES

- Attitudes toward Israelis/Palestinians, Jews/Muslims
- Example items:
    - "All [X] are responsible for their group's actions"
    - "When [Y] are violently attacked, it is because they deserve it."
- Hypothesis: Humanizing frames reduce prejudice
- Hypothesis: Effects concentrated among 'neutrals'

Table index

POLICY VIEWS

- Attitudes about:
    - Proportionality and justification of Israeli actions
    - U.S. military and humanitarian aid
- Hypotheses:
    - Human-cost frames → decrease support

Table index

EMOTION & MOBILIZATION

- Emotions: anger, sadness, helplessness, shame, despair
- Intended actions:
- Contact officials
    - Donate to Israeli or Palestinian causes
    - Willingness to attend protests

Table index