

Natural Language Processing for Maternal Healthcare: *Perspectives and Guiding Principles in the Age of LLMs*

Maria Antoniak

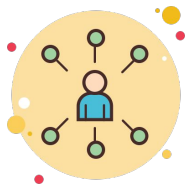
Allen Institute for AI



Research Overview

The goal of my research is to **use NLP and LLM tools creatively to study human experiences.**

I focus my research questions on:



people (e.g., members of online communities, healthcare workers)



subjective cultural concepts (e.g., narratives, values)



person-focused healthcare (e.g., maternal health, pain)

Cultural Analytics



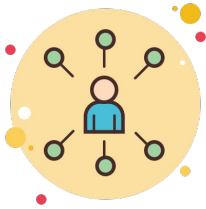
“the computational study of cultural objects, processes, agents”

(Journal of Cultural Analytics)

Traditional unsupervised NLP methods continue to be popular in cultural analytics research.

And now, LLMs are unlocking new ways to study human culture.

Computational analysis of storytelling



As a **rhetorical strategy**, storytelling can drive social movements (#MeToo, #BLM), spread misinfo (vaccine side effects), and educate (Ted Talks)



As a form of **self-disclosure**, personal storytelling can strengthen social bonds, build trust in a community, and benefit the storyteller's wellbeing



As a **sensemaking** strategy, communal storytelling can help individuals and groups learn from their shared (healthcare) experiences



For **NLP** researchers, modeling narratives is a very challenging task that is also important for better understanding our **pretraining** and **prompting** data

Person-Focused Healthcare



Biomedical NLP: information extraction, diagnosis prediction

Instead: text analysis for **online health support communities, LLM-based chatbot support, sensemaking strategies**

Narrative medicine lies at the intersection of the humanities, clinical practice, healthcare justice: “uses patients’ narratives to promote healing”

Yang, Kraut, Smith, Mayfield, and Jurafsky. “Seekers, Providers, Welcomers, and Storytellers: Modeling Social Roles in Online Health Communities.” CHI, 2019.

Ayers, Poliak, and Dredze. “Comparing Physician and Artificial Intelligence Chatbot Responses to Patient Questions Posted to a Public Social Media Forum.” JAMA, 2023.

Rita Charon. “Narrative Medicine: A Model for Empathy, Reflection, Profession, and Trust.”



Brief Intro to NLP

What is natural language processing?

NLP, or **computational linguistics**, uses computational methods to study human language.

This can include **analyzing** human language and **generating** human language.

Methods can include statistics, machine learning, linguistics, and programming.

Examples:

- Google Search
- Alexa
- Email spam filters
- Autocomplete
- ChatGPT

**“You shall know a word by the
company it keeps.”**

The **distributional hypothesis**, popularized by Firth (1957).

In other words: *Which words often appear together?*

We can learn about the **meaning** of a word by studying its **usage**.

In NLP, we often use a word's usage patterns as a **proxy** for its **semantic relationships** to other words.

What is a language model?

“a model that assigns a probability to sequences of words”

(Jurafsky & Martin, *Speech and Language Processing*)

Given a word sequence, can we **predict** the next word sequence?

What are “large language models”?

Also referred to as **pretrained models** and **foundation models**.

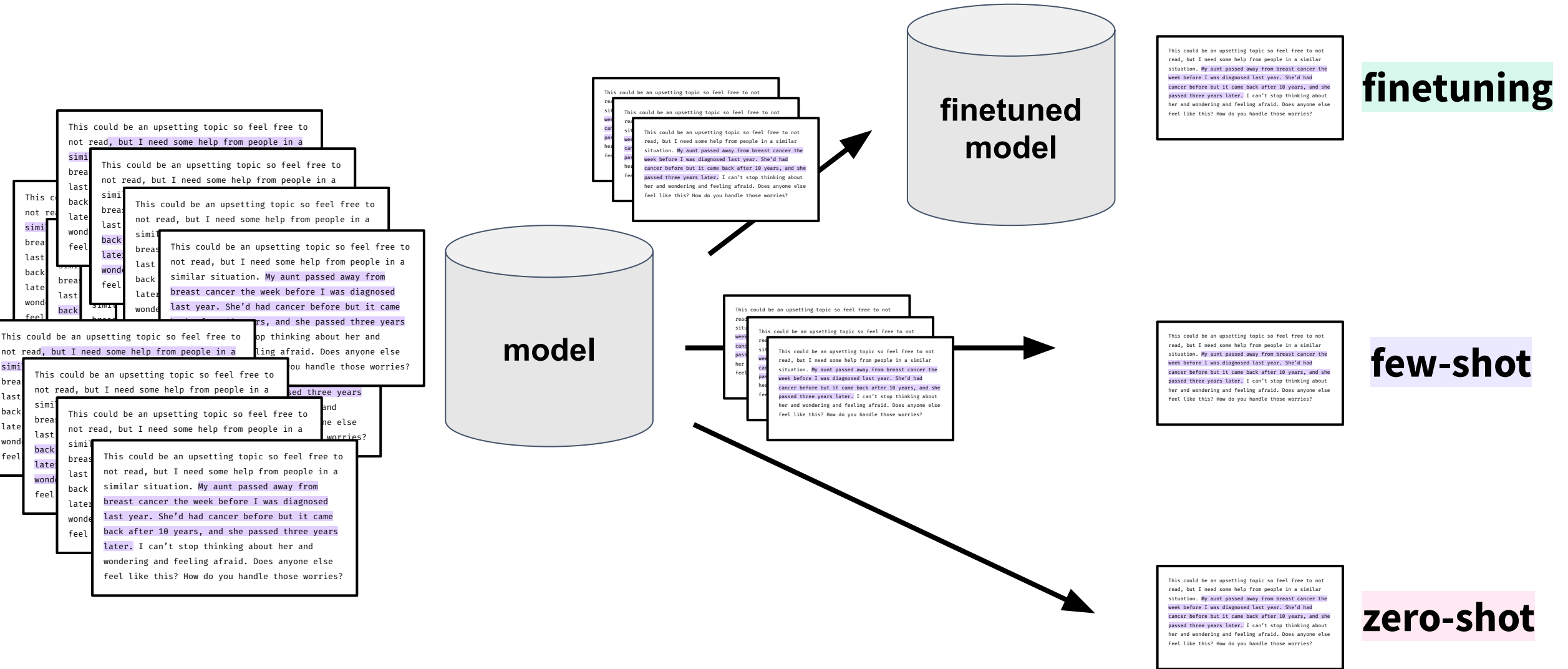
These models rely on **vast** collections of pretraining data.

Common sources include web scrapes, books, Wikipedia, Reddit, and scientific publications.

Some risks to keep in mind

1. Lack of interpretability
2. Giant datasets that are very difficult to document
3. Poor representation and quality for non-English languages
4. Toxicity/bias that is baked into the models

How do we use NLP models?



LLMs for Healthcare

Information Retrieval: Find all the EHRs with patients age 30-35

Prediction: Given this health history, how likely is postpartum depression?

Question Answering: General purpose tools for patients and providers

Linguistic Patterns: How do providers refer to different demographic groups?

→ We could use the same model for all of these tasks

→ Or we could use a smaller model customized to the individual task

Education & Tools

AI for Humanists

www.aiforhumanists.com

Stand-alone tutorials, references, and code for humanities researchers





NLP for Maternal Healthcare: Perspectives and Guiding Principles in the Age of LLMs

Maria Antoniak, Aakanksha Naik, Carla S. Alvarado, Lucy Lu Wang, Irene Y. Chen

FACCT 2024



Maternal Health Equity & NLP



This was a collaboration between the Allen Institute for AI, the University of Washington, UC Berkeley-UCSF, and the Center for Health Justice at the Association of American Medical Colleges (AAMC).

We gathered perspectives on LLMs from many different groups, and we developed guidelines for using NLP for maternal health.

Prior ethical guidelines



Chen et al and Wiens et al. overview the ML/NLP development pipeline and recommendations focused on each pipeline step. Mccradden et al. focus on ethical guidelines for ML-informed clinical decision-making.

The recommendations in these works are based on **literature reviews** and **broad sets of healthcare examples**.

Sendak et al. design guidelines based on the deployment of a specific sepsis-detection machine learning tool, and Petti et al. focused on developing ethical guidelines for the use of NLP and AI methods for early detection of Alzheimer's disease.

Guidelines for NLP for maternal health

We build on prior work that constructs ethical guidelines for machine learning practitioners by **narrowing** our focus.



NLP methods and applications, especially LLMs

Directly solicited perspectives from many affected groups

Focused on a specific healthcare topic: maternal health

Why maternal health?

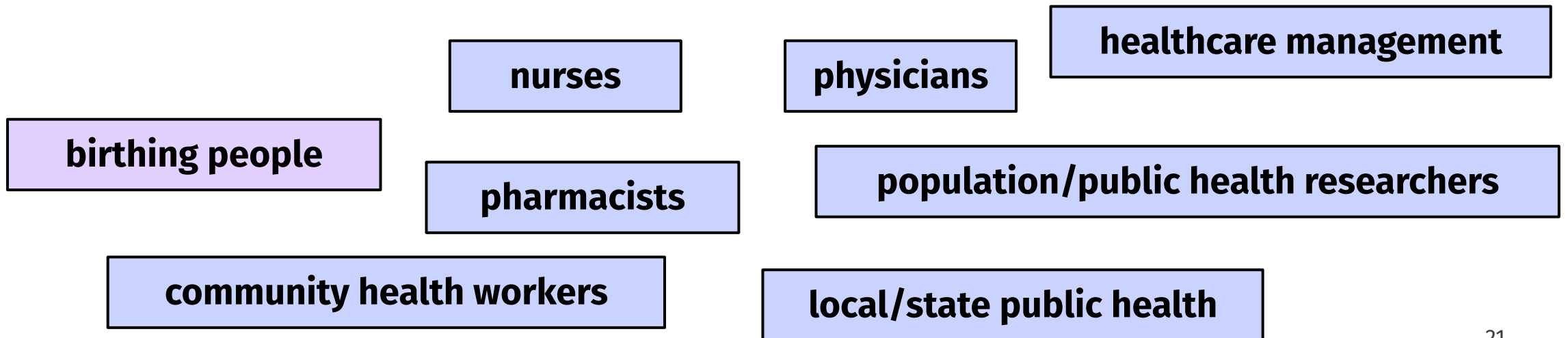


1. Many prior research studies and applications of NLP methods focused on maternal healthcare.
2. Pregnancy and childbirth are common events that often comprise a person's sole or major interaction with the healthcare system, increasing the significance and also abundance of perspectives on this topic.
3. Maternal health is a “perfect storm” of healthcare vulnerabilities, with historical biases and power dynamics influencing care.

Who should we ask?



We talked to many different stakeholders, including:



Elicit Perceptions from Stakeholders

medical workshop



236 participants (healthcare nonprofits, community health workers, public health researchers, etc.)



ChatGPT3.5 demo



survey and discussion

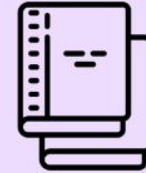
online platform



30 birthing people and 30 medical professionals (nurses, physicians, etc.)



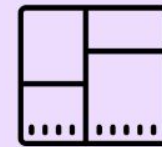
Analyze Data



literature review



compute statistics about participants and responses



aggregate common themes

Derive Guiding Principles

Theme 1: **Context**



Theme 2: **Measurements**



Theme 3: **Values**



MATERNAL HEALTH EQUITY WORKSHOP

FROM STORY TO DATA TO ACTION | MAY 18, 2023

FROM STORY TO DATA:
UNDERSTANDING
NATURAL LANGUAGE
PROCESSING

USING COMPUTATIONAL
METHODS TO STUDY HUMAN
LANGUAGE

WHAT IS
NLP?

from DATA TO MODEL

LANGUAGE MODELING

GIVEN A SEQUENCE OF
WORDS, CAN YOU PREDICT

THE NEXT
SEQUENCE
OF WORDS?

from STORY TO DATA

WORDS TO NUMBERS

147598
385374

YOU SHALL KNOW A
WORD BY THE
COMPANY IT KEEPS.
- FIRTH, 1957



SUPERVISED
AS WITH A CHILD,
WE SAY "DO THIS,
DON'T DO THAT"



UNSUPERVISED
COMPUTER FINDS
CODES, PATTERNS,
RELATIONSHIPS,
ON ITS OWN

from MODEL TO ACTION

QUAL

STORIES
METHODS
WORKING
TOGETHER
PATTERNS

QUANT



USING NLP TO IDENTIFY
STIGMATIZING LANGUAGE
CONTRIBUTING TO ADVERSE
HEALTH OUTCOMES

NLP ANALYSIS OF
EHR NOTES TO
DETERMINE BIASES



WHICH WORDS
OFTEN APPEAR
TOGETHER? → DEDUCE
MEANING FROM USAGE

CLINICAL RISK TOOL USING NLP

VITAL SIGNS
LAB VALUES
CLINICAL
DOCUMENTATION
MEDICAL HISTORY
DIAGNOSIS CODES



HIGH RISK
MORBIDITY
LOW RISK
PREGNANCY

FOR BETTER RISK STRATIFICATION

CONTENT ANALYSIS USING NLP



WHAT TOPICS
ARE PEOPLE
POSTING
ABOUT?
WHAT CAN
WE LEARN?

PEOPLE ARE GETTING
MATERNAL HEALTH INFO
FROM EACH OTHER BUT
NOT ALWAYS TALKING TO
A HEALTH PROVIDER.

USING NLP TO IMPROVE MATERNAL HEALTH

KENYA

I HAVE
QUESTIONS
ABOUT
PREGNANCY



"TRIM AI"
NLP FRAMEWORK
ANALYZES
URGENCY

RESULTS

- ✓ COST SAVINGS
- ✓ MORE ACCURATE
- ✓ REDUCED HELPDESK WORKLOAD

DIGITAL PLATFORM
CONNECTS BIRTHING
PEOPLE WITH LIFE-SAVING
HEALTH ADVICE

a RACE-CONSCIOUS
APPROACH

BEYOND
BUZZWORDS
REIMAGINING
THE DEFAULT
SETTINGS OF
TECHNOLOGY
& SOCIETY

✓ CODED BIAS
✓ IMAGINED OBJECTIVITY
✓ INNOVATION THAT
ENABLES CONTAINMENT
NEW "JIM CODE"

TAKE A
STEP BACK
AND ASK...
WHAT ARE THE NEEDS
OF BIRTHING
PEOPLE?

DON'T DISCOUNT
THE ANALOG SUPPORTS
THAT ARE ALREADY
WORKING
NOT ALL
SOLUTIONS
WILL BE
HIGH TECH
LIKE BLACK
BIRTH WORKERS!

SHOW
and
PROVE
THESE TOOLS
ARE NOT
HARMFUL
BEFORE
YOU DEPLOY
THEM

DESIGNERS
PROVIDERS
HOSPITALS
HEALTH CARE
SYSTEM
RESPONSIBILITY
TO
DO NO
HARM



FROM DATA TO ACTION:
WHAT HOSPITALS AND
HEALTH SYSTEMS CAN DO

NLP = NATURAL LANGUAGE PROCESS
EHR = ELECTRONIC HEALTH RECORD

BIAS IN BIAS OUT

TECHNOLOGY IS USEFUL
BUT
CONTEXT IS KEY:
LISTEN TO
BIRTHING PEOPLE!

Ask a question

Think of a situation when a person might have questions about maternal health.

Ask a question related to this situation. Then click Submit to generate a response.

For example:

- *What is the difference between preterm labor and Braxton Hicks contractions?*
- *What is the newest research about the relationship between air pollution and preterm labor?*

Please ask at least five new questions. You can edit your question and click Submit to generate a new response.

⚠ Don't include any private information like real names or dates. ⚠

⚠ Always check with a healthcare professional before making any healthcare decision. ⚠

Question *

What is the difference between preterm labor and Braxton Hicks contractions?

Submit

 OpenAI Response:

Preterm labor and Braxton Hicks contractions are two different conditions related to contractions during pregnancy: 1. Preterm labor: This refers to the onset of regular contractions before 37 weeks of pregnancy. It is also known as premature labor or premature

Tell us what you think

What do you think about this response? Check all that apply.

- This response is accurate.
- This response is trustworthy.
- This response is useful.
- This response is up to date.
- I'm not sure what to think about this response.

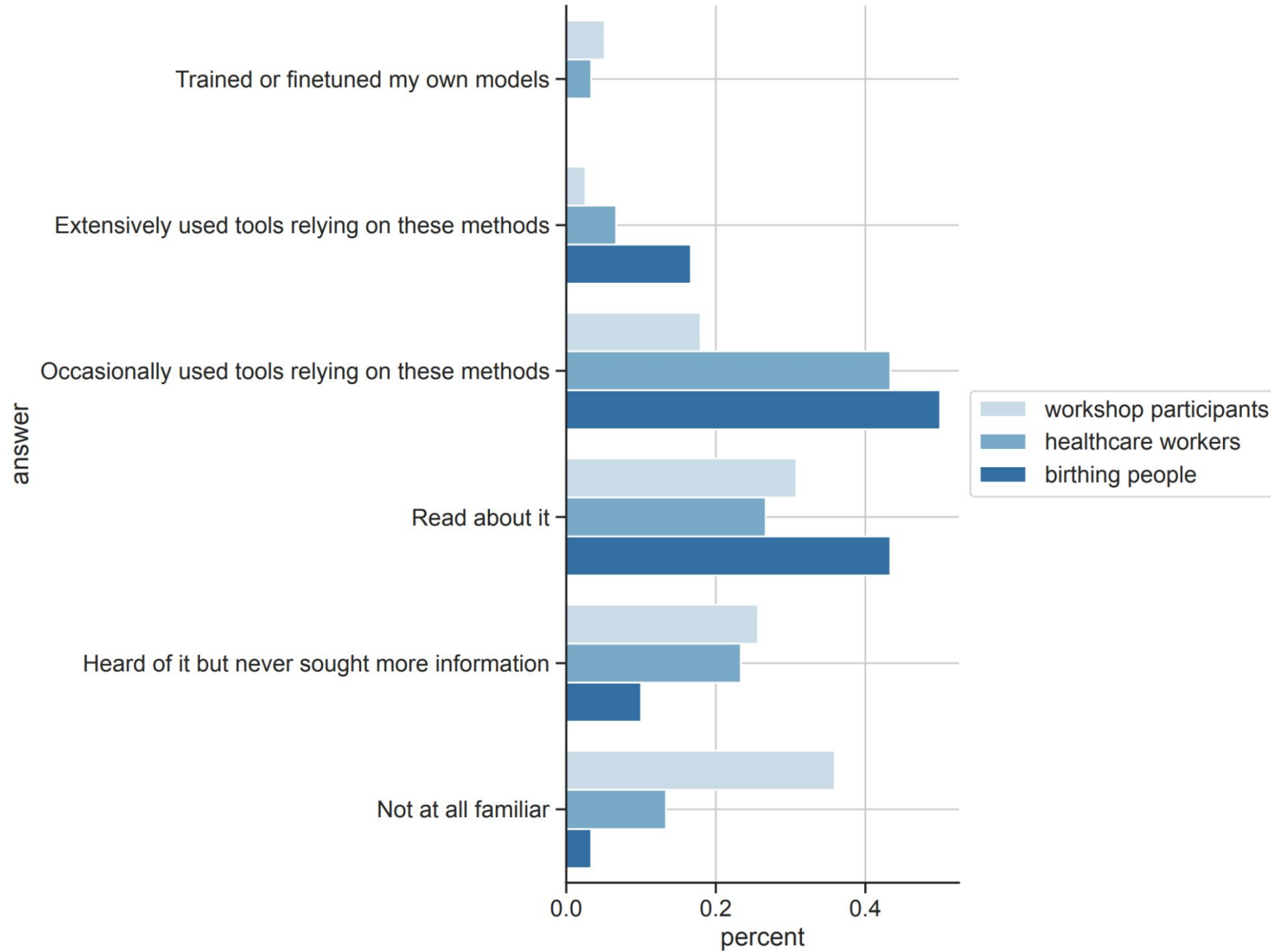
Notes

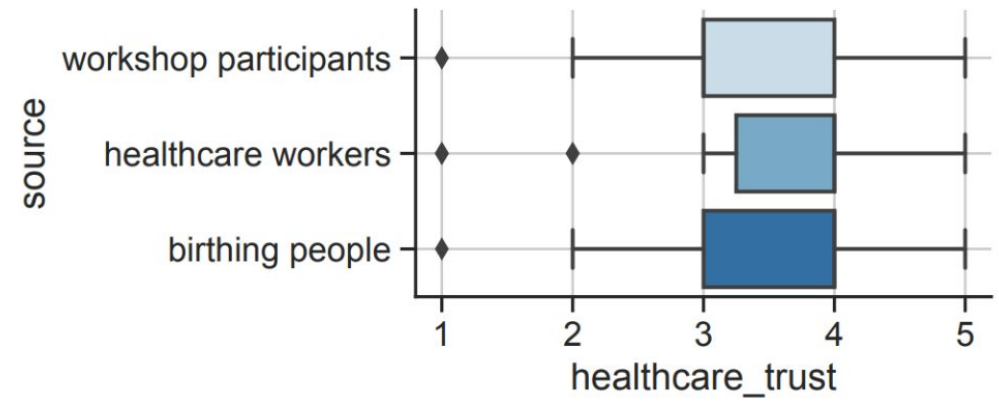
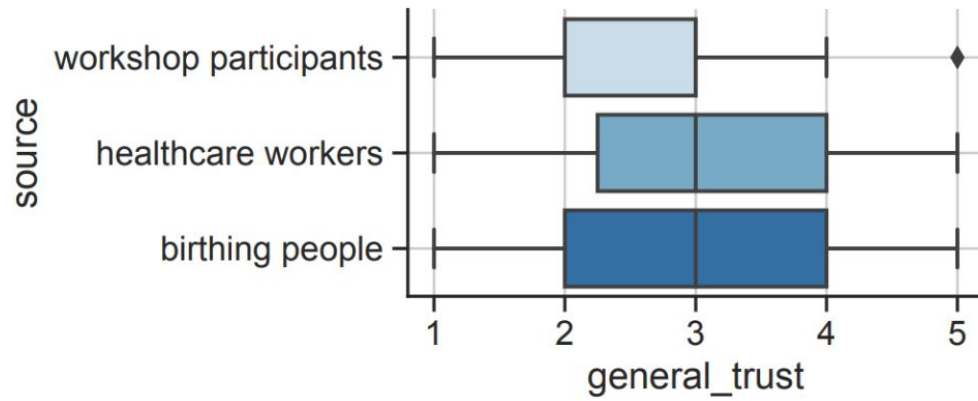
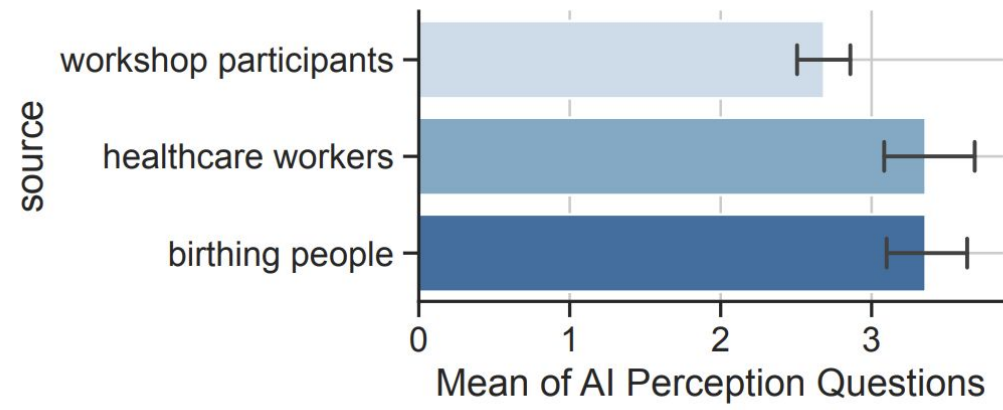
Submit



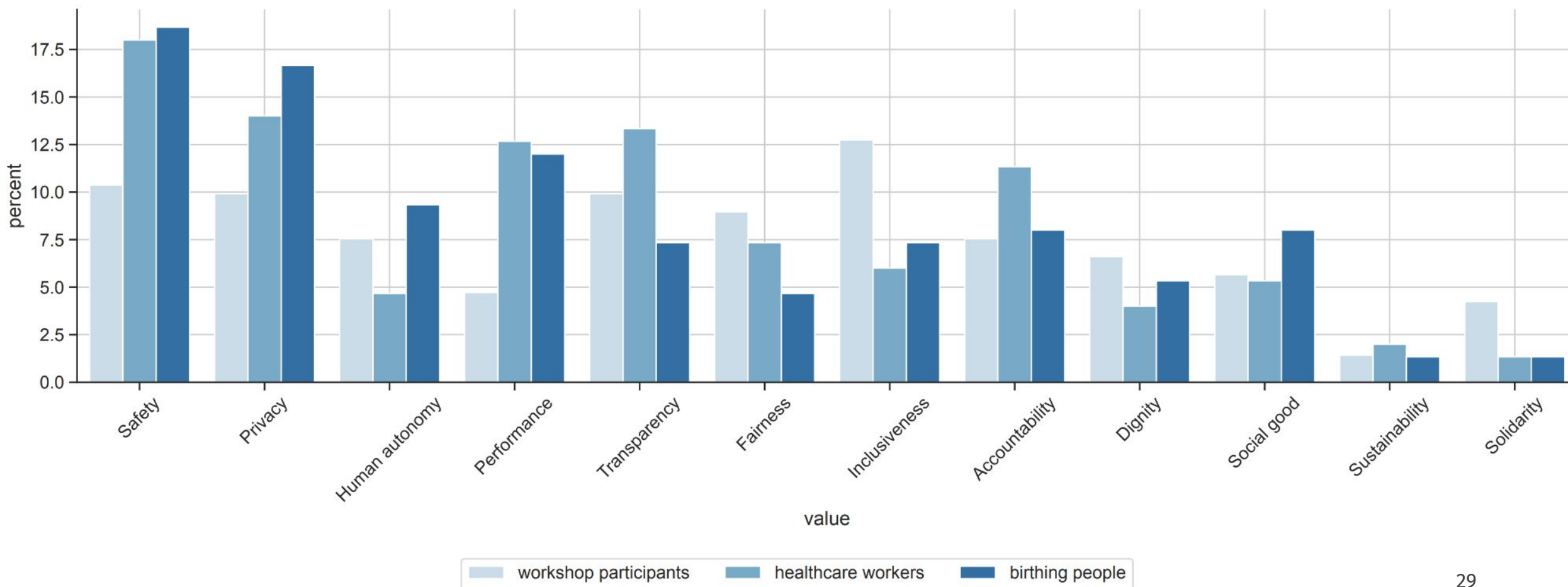
1. How was your experience with the chatbot? What stood out to you about the responses?
2. What are your dream NLP tools for maternal health? What tools should never be built?
3. Which maternal health stakeholders (birthing people, nurses, doulas, etc.) would benefit or be hurt by NLP tools?
4. What principles should guide the use of NLP for maternal health? What should be the goals and guardrails?

| Cohort | Race/Ethnicity | Age | Highest Education | Gender |
|--|-----------------------------|------------|-----------------------------|---------------|
| <i>Workshop Participants (N = 39)</i> | | | | |
| 38% community nonprofits | 41% African-American/Black | 35% 35-44 | 38% MS, MPH, etc. | 92% women |
| 27% pop./public health research | 41% White | 30% 25-34 | 30% PhD | 5% men |
| 24% comm. health/promotara | 16% Hispanic/Latino/a/x | 19% 45-54 | 24% BA, BS, etc. | 3% no answer |
| 24% local/state public health | 5% South Asian | 11% 55-64 | 11% <i>all other groups</i> | 0% non-binary |
| 19% healthcare management/admin | 19% <i>all other groups</i> | 5% 65-74 | | |
| 16% healthcare services researcher | | | | |
| 11% other perinatal healthcare provider | | | | |
| 11% other non-healthcare perinatal support | | | | |
| 8% doula | | | | |
| 8% non-perinatal healthcare provider | | | | |
| 13.5% <i>all other groups</i> | | | | |
| <i>Healthcare Workers (N = 30)</i> | | | | |
| 20% nurse | 57% White | 33% 35-44 | 50% BA, BS, etc. | 79% women |
| 17% pharmacy | 23% African-American/Black | 30% 25-34 | 17% MS, MPH, etc. | 21% men |
| 10% physician | 7% East Asian | 10% 18-24 | 17% Trade School | 0% non-binary |
| 10% medical tech | 7% Southeast Asian | 3% 65-74 | 10% MD, DO, etc. | |
| 10% medical assistant/aide | 9% <i>all other groups</i> | 3% 55-64 | 7% Community College | |
| 10% research | | | 6% <i>all other groups</i> | |
| 23% <i>all other groups</i> | | | | |
| 33% have worked in maternal/perinatal healthcare | | | | |
| <i>Birthing People (N = 30)</i> | | | | |
| 20% have worked in healthcare | 73% White | 53% 25-34 | 33% BA, BS, etc. | 97% women |
| 7% have worked in maternal/perinatal healthcare | 20% Hispanic/Latino/a/x | 37% 35-44 | 30% High school or | 7% non-binary |
| | 17% African-American/Black | 10% 65-74 | GED | 0% men |
| | 12% <i>all other groups</i> | | 13% Community | |
| | | | College | |
| | | | 10% MS, MPH, etc. | |
| | | | 10% Trade School | |
| | | | 7% PhD | |
| | | | 3% Prof. Degree | |

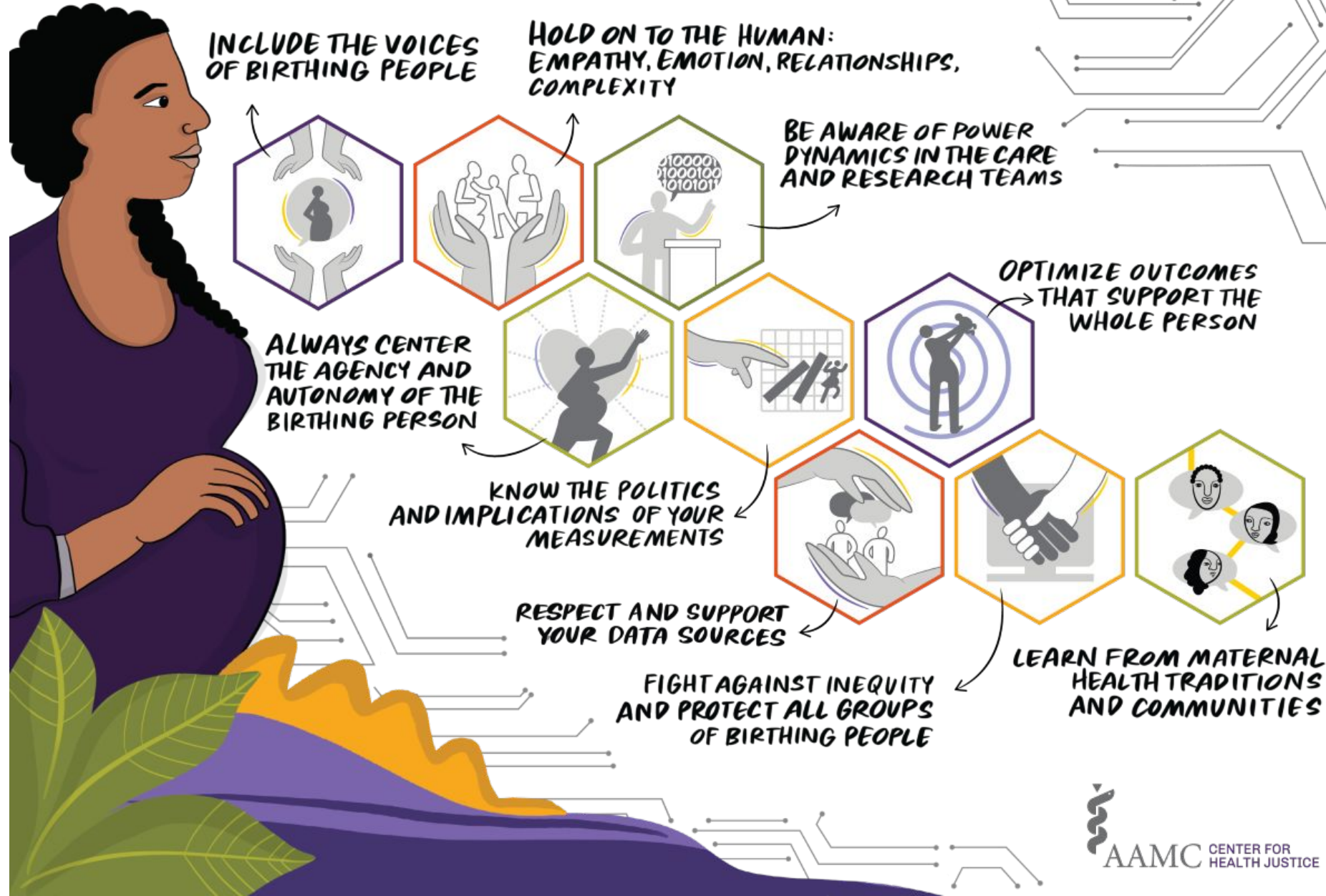




Different groups prioritize different values



FOUNDATIONS OF RESPONSIBLE NLP USE FOR MATERNAL HEALTH EQUITY



Guidelines: Recognizing contextual significance

Be aware of power dynamics in the care team.

“If mothers relied too heavily on AI instead of seeking professional help then the nurses and doulas may see fewer people seeking care” – *Birthing Person 11*

Know the politics and implications of your measurements.

“I get worried about what’ll happen when insurance companies think there’s cost savings to using these tools ... they can cut corners, have more profit ... given the incentives in ... the healthcare system” – *Workshop Participant 1*

Learn from maternal health traditions and communities.

“It [(AI)] should follow the same guidelines that medical professionals do: ‘Do no harm.’ ” – *Healthcare Worker 6*

Guidelines: Holistic measurements

Optimize for outcomes that support the whole person.

“It’s not just about the outcome, right? It’s about the whole experience” – *Workshop Participant 3*

Protect all groups of birthing people.

“Everything that has the potential to benefit also has the potential to hurt” – *Workshop Participant 4*

Hold onto the human: empathy, emotion, relationships, complexity

“your own judgment and/or human compassion components, wisdom, experience [are a] part of the care” – *Workshop Participant 7*

Guidelines: Who and what is valued

Include the voices of those seeking care.

“there needs to be community input, there needs to be representation in creating these tools”
– *Workshop Participant 8*

Always center the agency and autonomy of the birthing person.

“[Disclose explanations so that] the person using it knows what kind of information or advice it can and cannot give” – *Birthing Person 2*

Respect and support your data sources.

“The principle that should guide these tools is to... have transparency for its sourcing of data”
– *Healthcare Worker 2*

Perceptions of risks and benefits of LLMs

“I wish it [(AI)] had been around when my son was a newborn so I could interact with it during late night feedings. One, to give me something to do, and two, **to make me feel like I wasn't alone**” – *Birthing Person 12*

“**Just to have something there** to ask questions to when I am not sure as to what is happening or when I need a quick answer” – *Birthing Person 9*

LLMs as part of an information ecosystem

“Often times people will **google questions and try to sift through all the search results** to find the applicable information. AI could make that a much more efficient process” – *Healthcare Worker 9*

“It would be nice to be able to type in **worries and fears** to an AI bot and get accurate answers **instead of going down rabbit trails on search engines** that leave you more concerned” – *Birthing Person 11*

“People already diagnose themselves on WebMD. Providing more tools can be **dangerous**” – *Birthing Person 4*

Next Steps

Examining our collected query data!

Small but high quality query dataset written by diverse stakeholders and professionals about a specific healthcare topic.

Expand this data? Combine with another dataset? Measure empathy in responses?

| THEME | COUNT |
|---------------------------------------|-------|
| pregnancy | 45 |
| best practices | 43 |
| symptom interpretation | 38 |
| labor | 34 |
| risks | 26 |
| pain | 21 |
| weighing options | 19 |
| definitions and information | 15 |
| finding resources | 15 |
| inequity | 15 |
| dismissal | 14 |
| care team | 13 |
| race | 13 |
| what to expect | 12 |
| is this normal | 11 |
| breastfeeding | 10 |
| fear | 10 |
| postpartum | 9 |
| planning communication with providers | 8 |
| finances | 7 |
| first time pregnancy | 7 |
| blood pressure | 5 |

Themes: *Seeking definitions and information*

| SITUATION | QUESTION |
|--|---|
| A patient is approaching her due date and her doctors has recommended an induction because of her age if she does not go into labor spontaneously. She has had 3 vaginal deliveries with no complications. | What is a labor induction? |
| An analyst is interested in learning about different maternal health indicators. | How do Nulliparous, Term, Singleton, and Vertex Cesarean Birth Rates inform maternal health? |
| A patient is worried about not knowing the difference between preterm labor and or Braxton Hicks contractions. They're experiencing some contractions but they aren't sure what to do next. | What is the difference between preterm labor and Braxton Hicks contractions? |
| Patient doesn't know whether they want a natural birth or induced | How often is pitocin used |
| A researcher is interested in learning more about racial inequities in maternal health. | What are racial inequities? |
| Women entering prenatal care late | How do we define late entry to prenatal care for a pregnant patient? |
| entering late into prenatal care | how do you define late entry to prenatal care? |
| A pregnant patient is concerned about back pain she is experiencing and wants to know if it is sciatic pain or contractions. | What is the difference between sciatic back pain and contractions? |
| When they are having vaginal discharge. Often women are concerned about whether it is was normal or not. | What is the difference between vaginal discharge in pregnancy and rupture of membrane? |

Themes: *Planning communication with provider*

| SITUATION | QUESTION |
|---|---|
| <p>A first time mother is worried about pelvic pain but has been told that this is just something all pregnant mothers experience. It has become difficult for her to sleep at night and feel rested for work the next day. She is at her appointment with a new provider and considering sharing what she has been feeling but is hesitant because she has been ignored by providers in the past.</p> | <p>Is pelvic pain normal for first time mothers?</p> |
| <p>A patient is expressing concerns about a procedure and its associated risks. They have had negative experiences before and wants to make sure she is making an informed decision about her options. During this process, she feels like she is not being listened to.</p> | <p>What are the pros and cons of each of the c-section option that you are presenting to me?</p> |
| <p>A middle eastern pregnant patient is nervous because her doctor is dismissive of her feeling and symptoms.</p> | <p>I am middle eastern and my doctor keeps dismissing my symptoms, how do I make my doctor take me seriously?</p> |
| <p>Karen is 24 weeks gestation, and reports to her OB/GYN that her mouth is bitter and she is not able to eat. While the OB/Gyn is concerned about Karen's not gaining weight according to her gestational age, he is not addressing Karen's concerns.</p> | <p>How can I elevate my concerns as priorities?</p> |
| <p>Patient is 39 weeks pregnant and provider wants to induce labor. Patient wants to wait until 41 weeks for spontaneous labor.</p> | <p>I want to wait for spontaneous labor until 41 weeks and my provider wants to induce me at 39 weeks. I do not want an induction. What should I say to my provider.</p> |



Narrative Paths and Negotiation of Power in Birth Stories

Maria Antoniak, Karen Levy, David Mimno

Computer-Supported Cooperative Work (CSCW), 2019



A maternal mortality crisis in the U.S.

In the U.S., rates of pregnancy-related deaths and complications are rising but many of these are potentially **preventable**.

Berg et al. "Preventability of pregnancy-related deaths: results of a state-wide review." *Obstetrics & Gynecology*, 2005.

Creanga et al. "Pregnancy-related mortality in the United States, 2006-2010." *Obstetrics & Gynecology*, 2015.

Postpartum depression affects 6-13% of people after childbirth, but it can be **prevented or mitigated**.

Lavender & Walkinshaw. "Can midwives reduce postpartum psychological morbidity? A randomized trial." *Birth*, 1998.

Stewart & Vigod. "Postpartum Depression." *New England Journal Medicine*, 2016.

Research Questions

Negative birthing experiences are associated with a **loss of control**.

NLP methods let us explore birthing people's voices **at scale**.

We use **quantitative measurements** to add **qualitative detail** to prior work on birthing experiences and decision making.

Carma L Bylund. "Mothers' involvement in decision making during the birthing process: a quantitative analysis of women's online birth stories." *Health Communication*, 2005.

Online Birth Stories

Detailed personal narratives of giving birth that have been shared throughout history and are very popular (but under-studied) online.



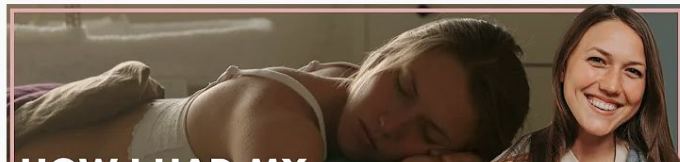
my birth story + meet baby girl #2 | Aspyn Ovard

196K views • 1 month ago



Aspyn Ovard ✓

video edited by: Tala Alharbi talaeditss@gmail.com intro by: @typehayley FOLLO



My Positive BIRTH STORY + TIPS For Giving Birth With

613K views • 10 months ago



Bridget Teyler ✓

All podcasts for "birth story"



The Birth Hour - A B...

Bryn Huntpalmer



Birth Story Podcast

Heidi Snyderburn



The Positive Birth S...

Åsa Holstein



Healing Birth

Diana Forsell Tayan



Birth Stories in Color

Laurel Gourrier & Danielle Jackson



High Risk Birth Sto42

High Risk Birth Stories

Research Questions



What narrative **pathways** are described in birth stories?
How are **expected** or **unexpected** event sequences **framed**?



Whom do the authors frame as holding **power**?
What **actions** do these actors take that makes them powerful?



r/BabyBumps: Post Titles

- ❖ Fiona's **Birth Story**: The best laid plans go awry? Long read
- ❖ Thomas Berry **Birth Story** (Planned C-Section w/Complications)
- ❖ John's **Birth Story** - (planned for natural birth, got an ER c-section)
- ❖ Emily Rose's **Birth Story**
- ❖ My **birth story**! [home, unmedicated, midwife-assisted water-birth]
- ❖ Damian's Home**birth Story**!
- ❖ Alice's **birth story**. (long, didn't go as planned)

“I’ll begin just by saying that this subreddit has taught me so much in preparation for my first birth. I gained a lot of insight into other people’s experiences, and I loved reading all the stories, whether positive or negative. I hope that sharing my story helps someone in the same way.

“It was 1AM, April 5th. I was experiencing some light cramping and couldn’t fall asleep. This was pretty normal since 39 weeks, so I wasn’t worried. My husband woke up and was rubbing my back when I felt a pop. I told my husband, and he thought it was just my back cracking, but I realized that it was my water breaking. I told my husband that it looks like it’s time to go to the hospital! It was 3:30AM at that point.

“We headed to the hospital and got admitted. The nurse checked me, which was extremely painful, to the point that I wanted to cry. She said that I wasn’t even one centimeter dilated, which didn’t surprise me because I was supposed to be induced on April 8th. They got me started on pitocin to help start contractions and moved me to the delivery room at 4:45AM ... ”

r/BabyBumps: Ethical Tensions



Need to consider:

- Privacy tradeoff
- Setting and context
- Who is most vulnerable

Our decisions for this dataset:

- Paraphrase all quotes
- No data release
- Share our findings on r/BabyBumps

Narrative Patterns: Topics Over Time

We trained a latent Dirichlet allocation (LDA) **topic model** on the stories.

LDA is an unsupervised, generative model that produces a **probability distribution over words** for each topic and a **probability distribution over topics** for each document.

LDA continues to beat other topic modeling methods (including LLM-based methods!) in human coherence tests.

Blei et al. “Latent Dirichlet allocation.” *JMLR*, 2003.

Harrando et al. “Apples to Apples: A Systematic Evaluation of Topic Models.” RANLP, 2021.

Hoyle et al. “Are Neural Topic Models Broken?” Findings of EMNLP, 2022.

Story Time

0.10 I'll begin just by saying that this subreddit has taught me so much...

0.20 It was 1am, April 5th. I was experiencing some light cramping...

0.30 We headed to the hospital and got admitted. The nurse checked me ...

...

Topic 1

Topic 2

Topic 3

Topic 4

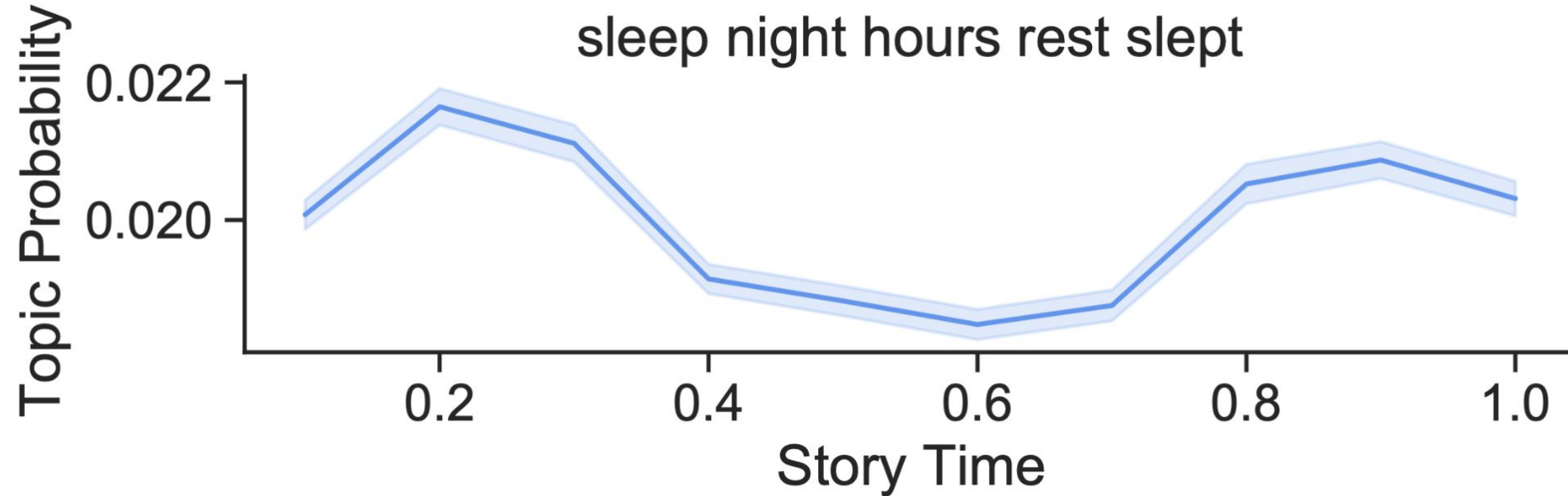
[0.01, 0.20, 0.03, 0.56, ...]

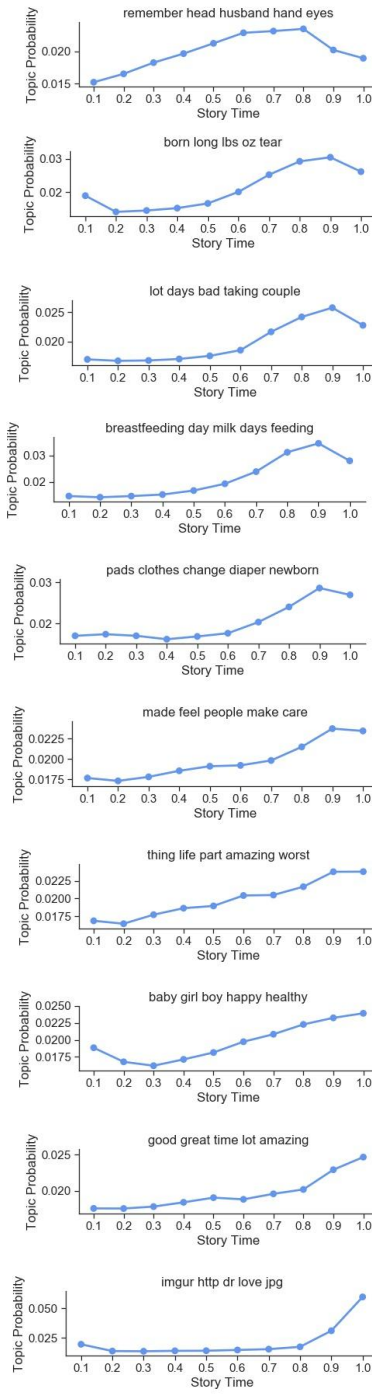
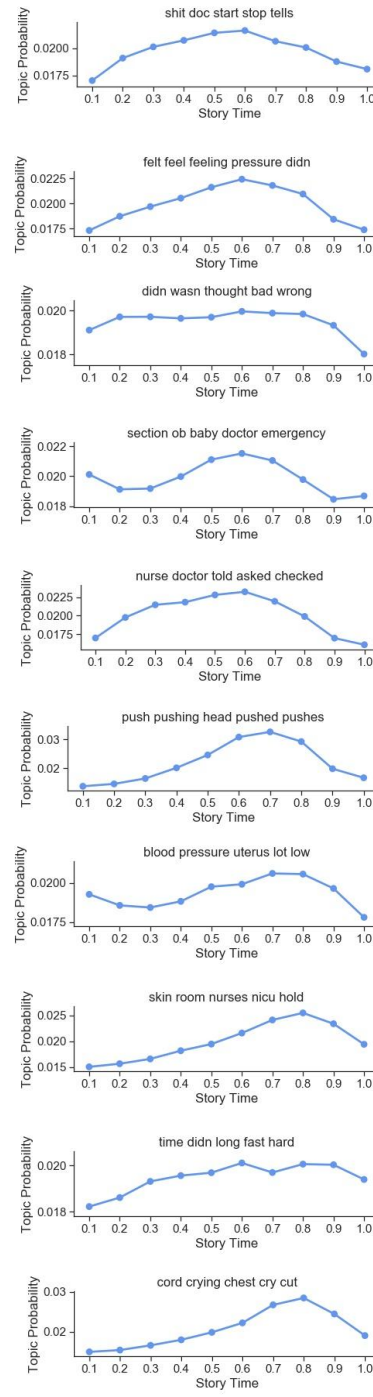
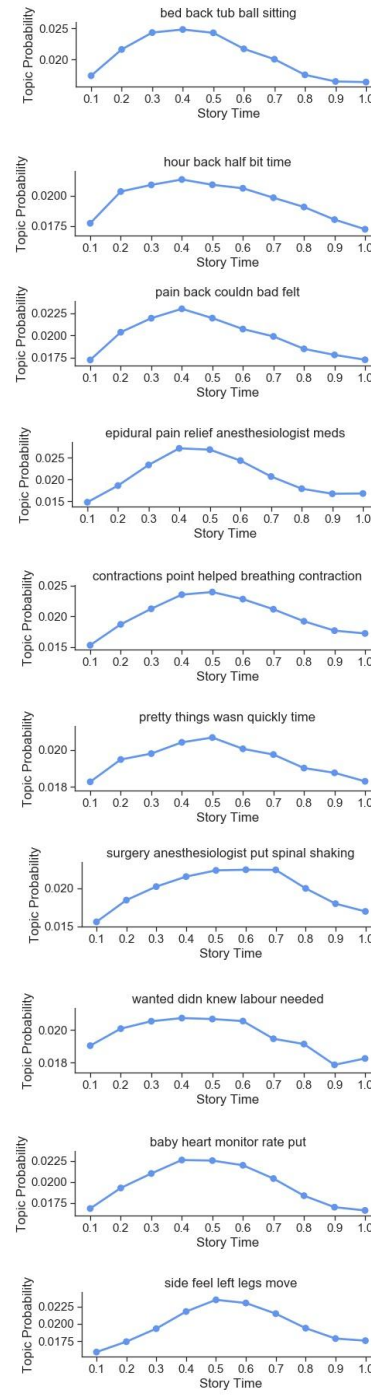
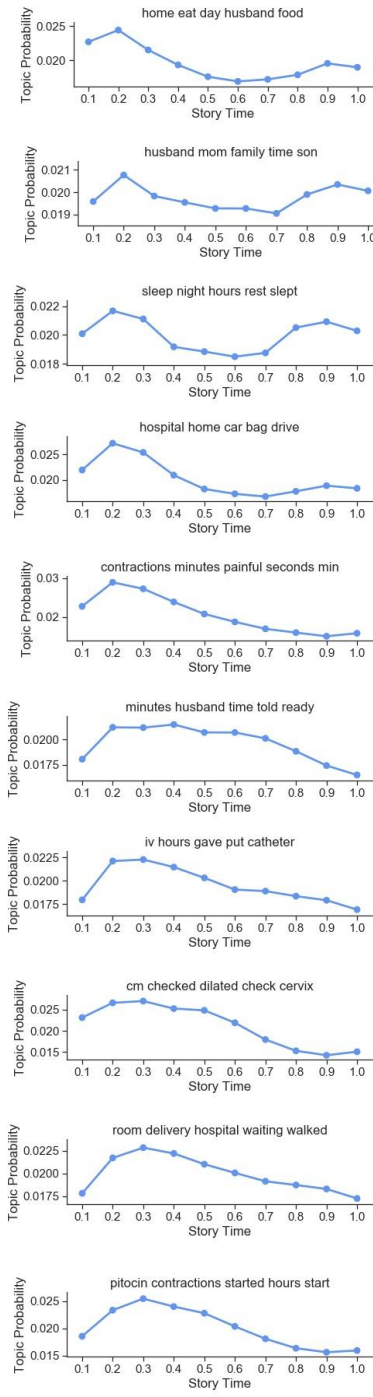
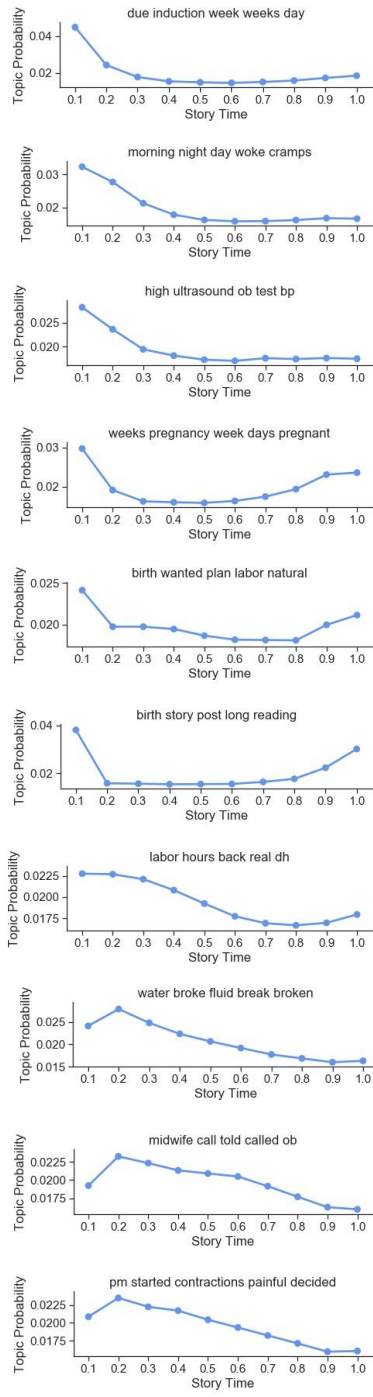
[0.23, 0.11, 0.02, 0.01, ...]

[0.03, 0.01, 0.32, 0.04, ...]

...

Narrative Patterns: Topics Over Time





Story Time

0.10 I'll begin just by saying that this subreddit has taught me so much...

0.20 It was 1am, April 5th. I was experiencing some light cramping...

0.30 We headed to the hospital and got admitted. The nurse checked me ...

...

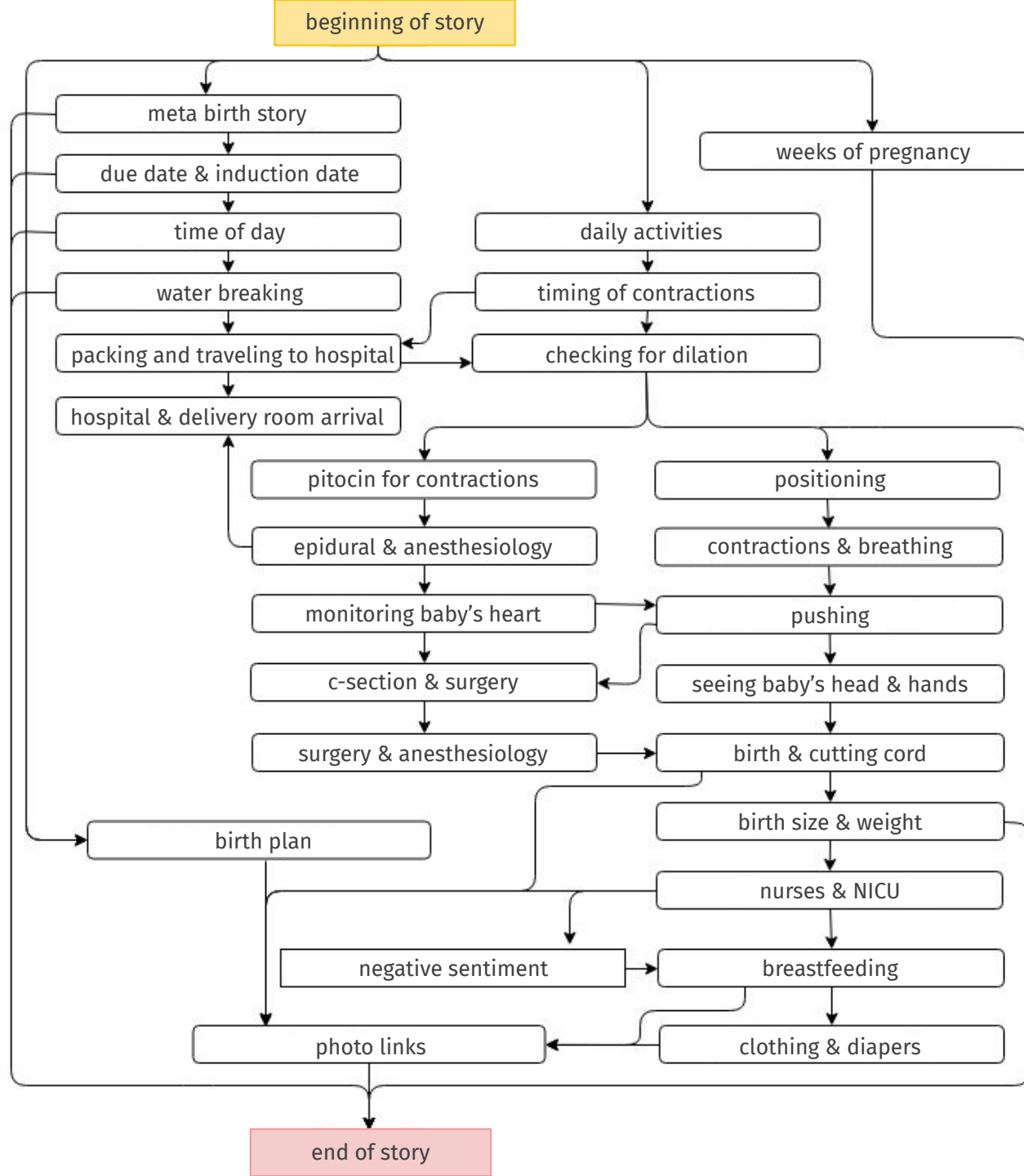
Topic 1 Topic 2 Topic 3 Topic 4

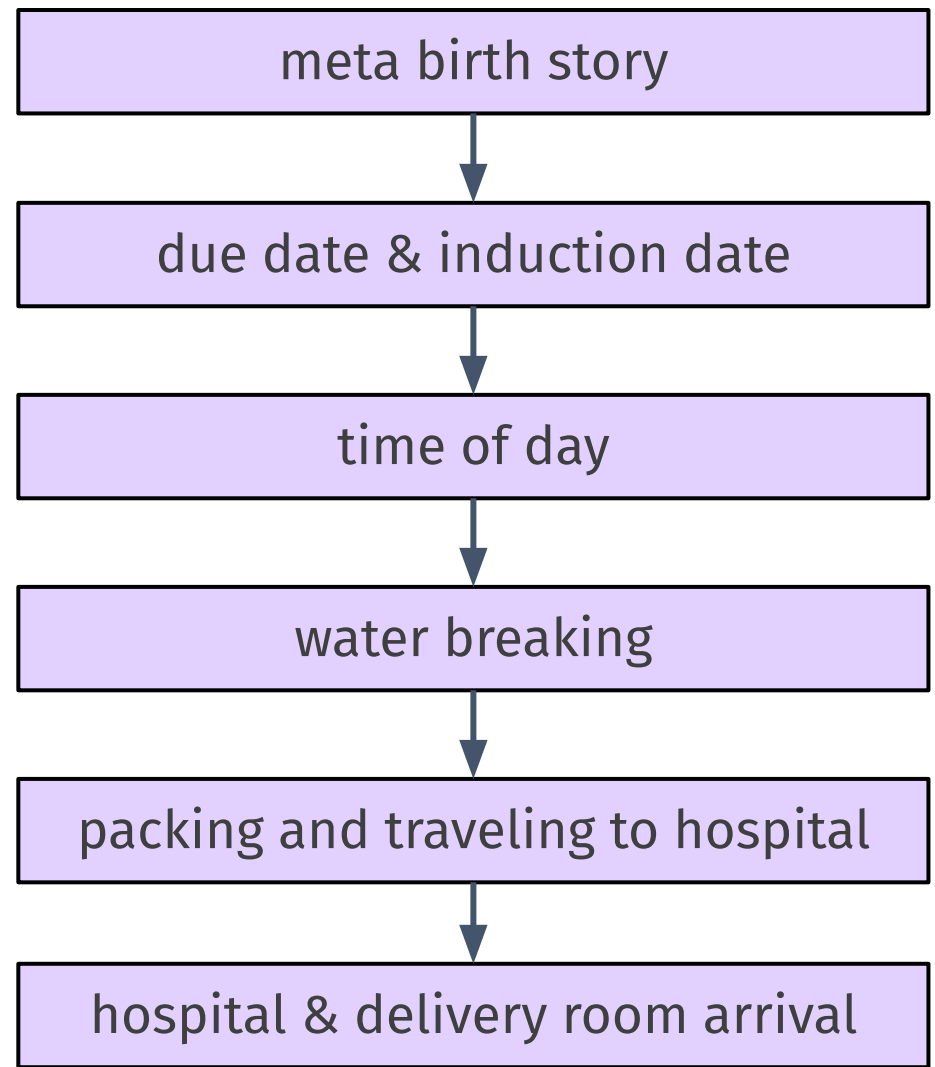
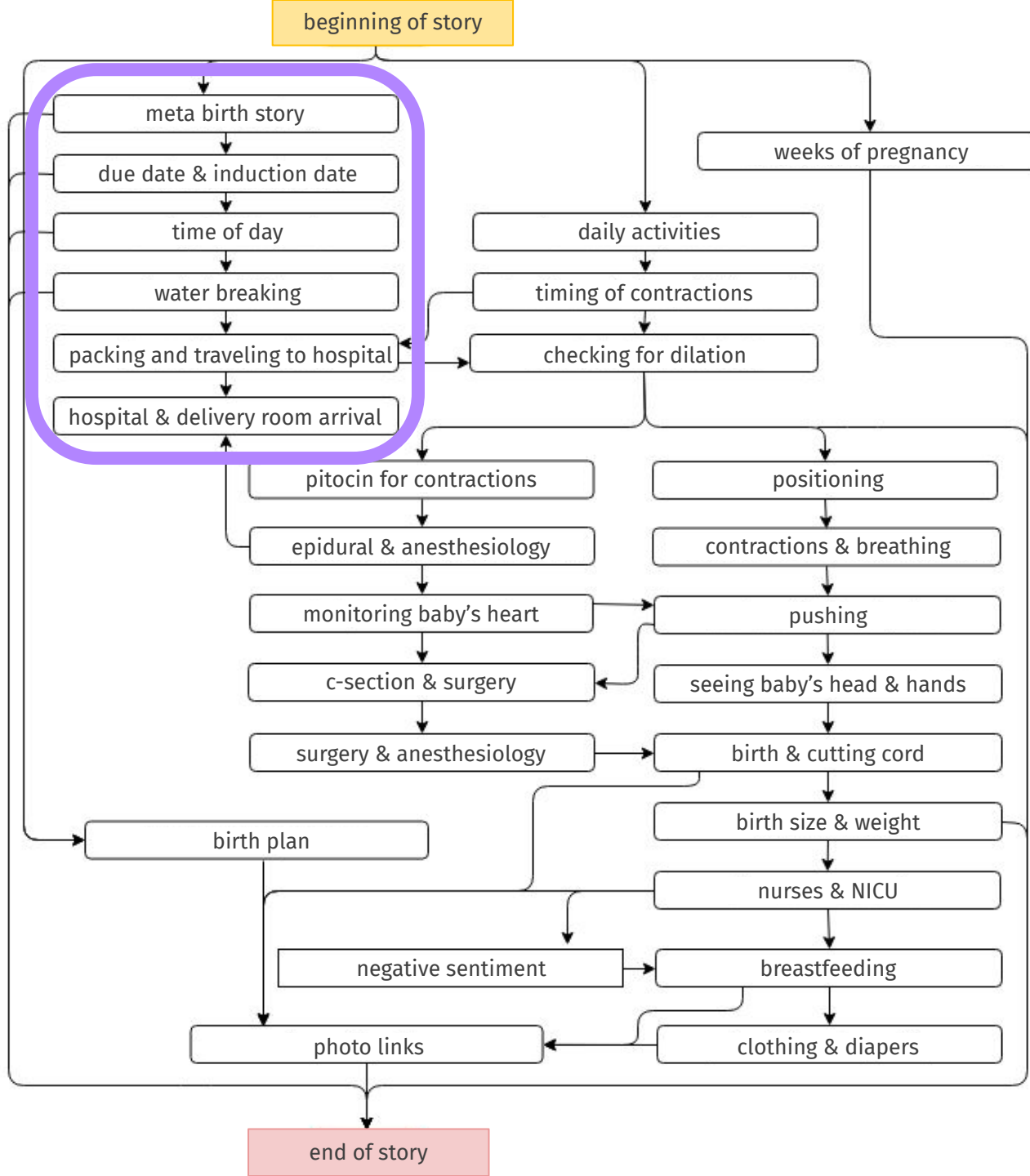
[0.01, 0.20, 0.03, 0.56, ...]

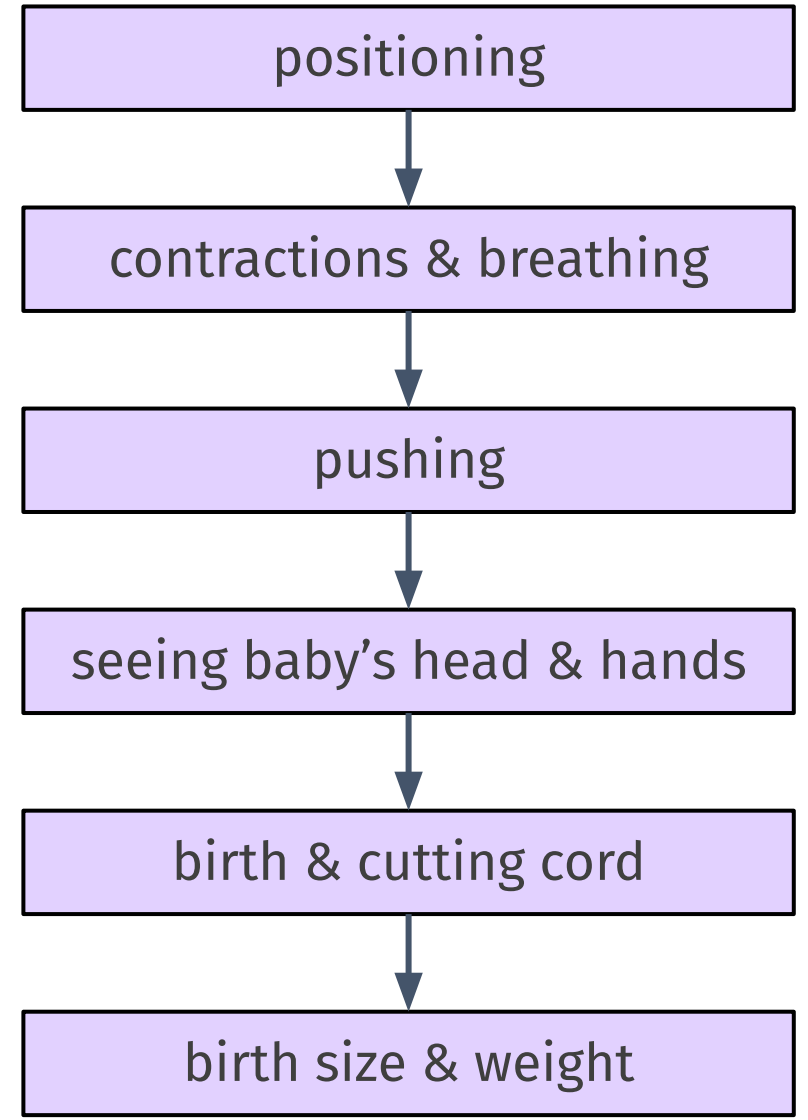
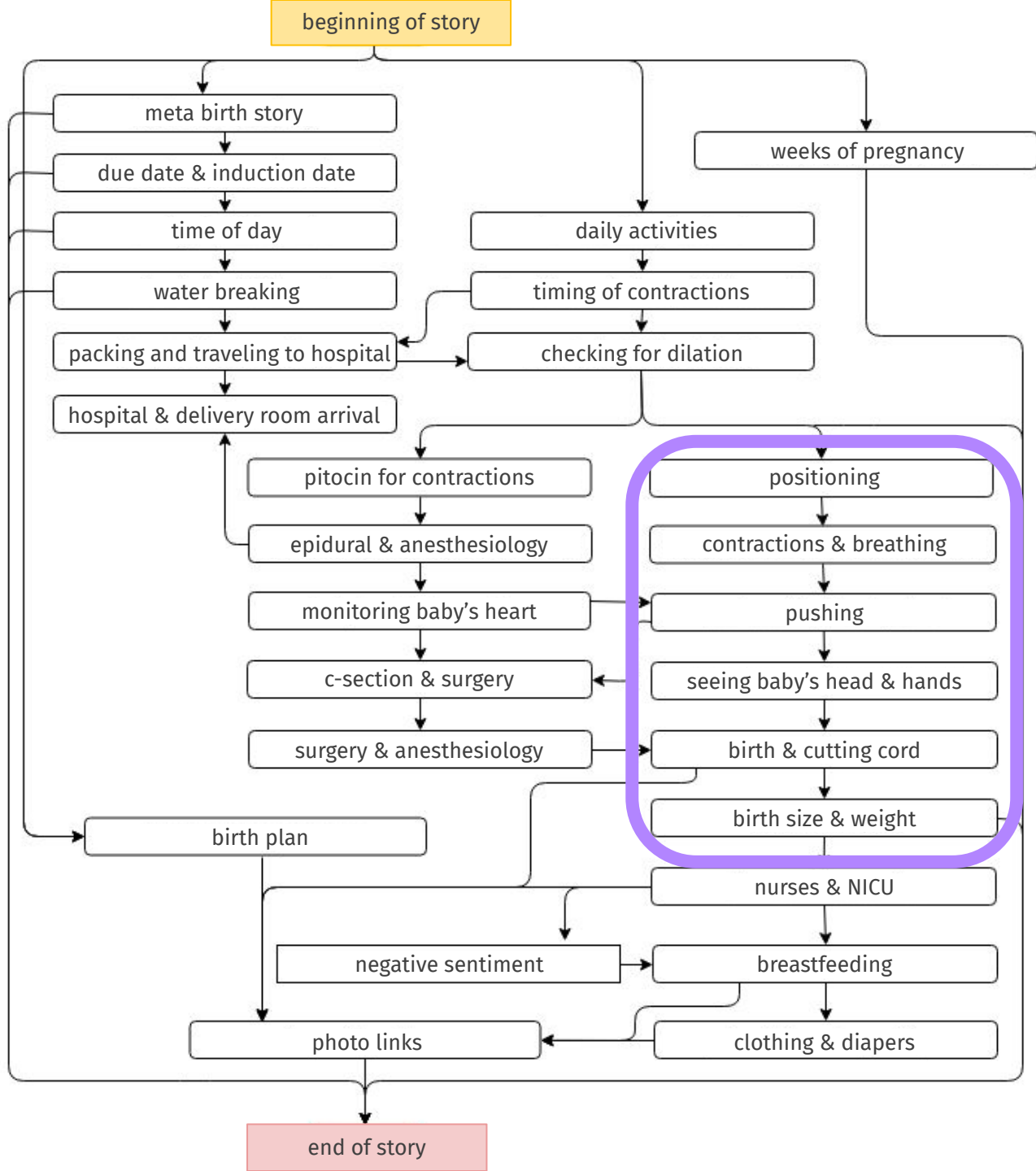
[0.23, 0.11, 0.02, 0.01, ...]

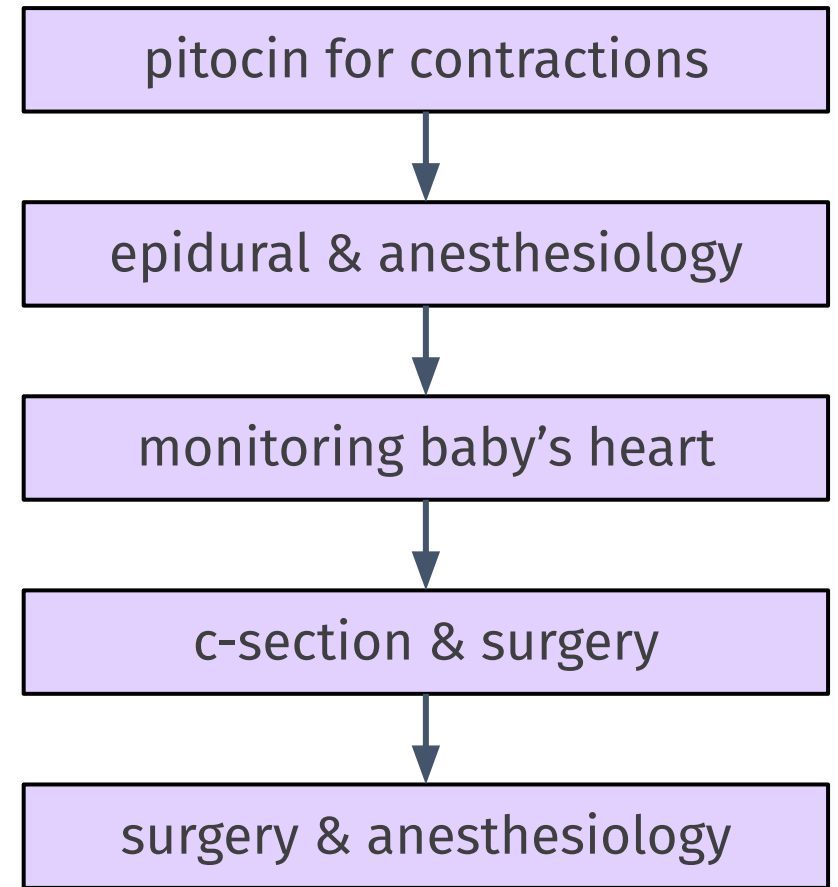
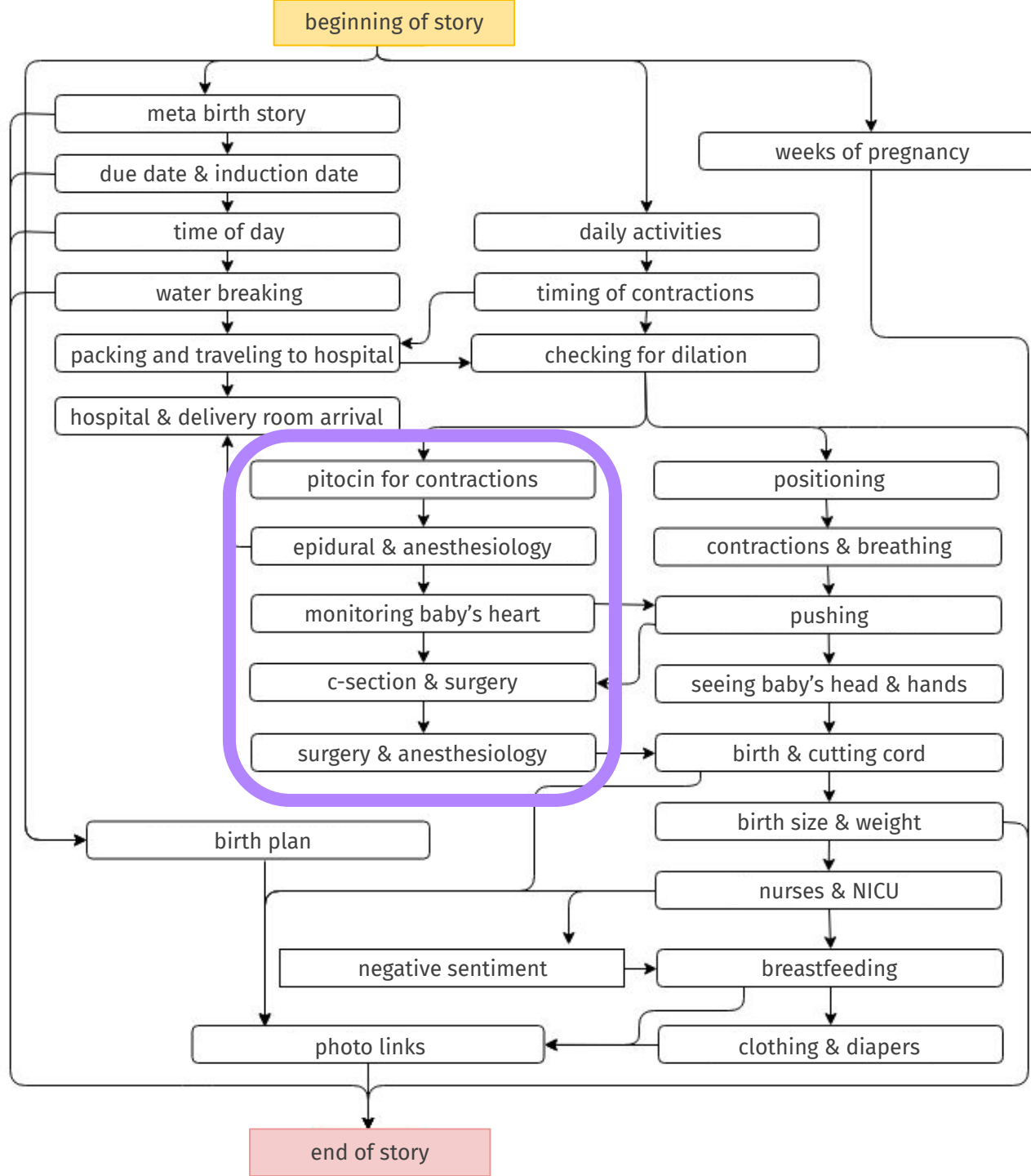
[0.03, 0.01, 0.32, 0.04, ...]

...









My **positive medicated** birth story

Jonah's birth story: **positive, medicated, c-section**

My **positive medicated** birth story

Topic 11

Topic 32

Topic 5

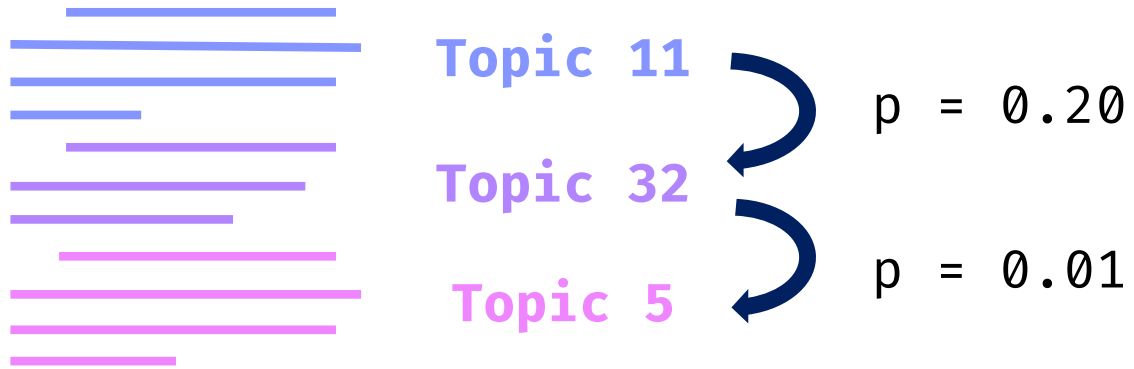
Jonah's birth story: **positive, medicated, c-section**

Topic 47

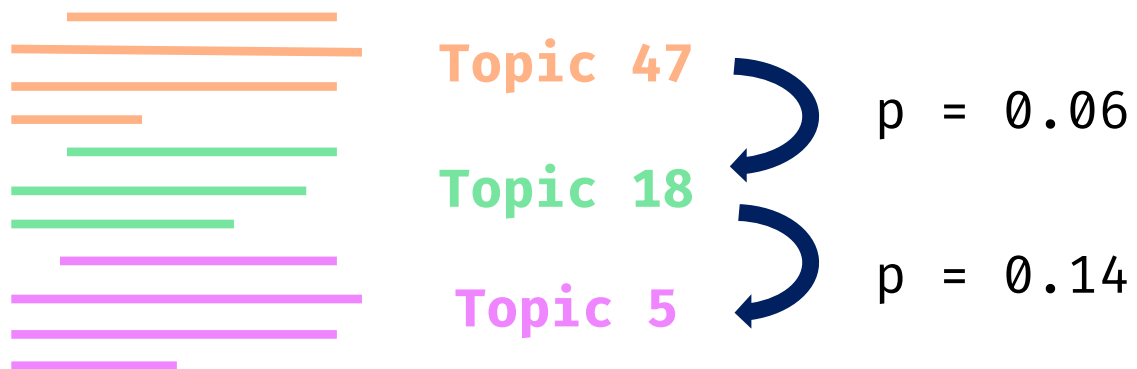
Topic 18

Topic 5

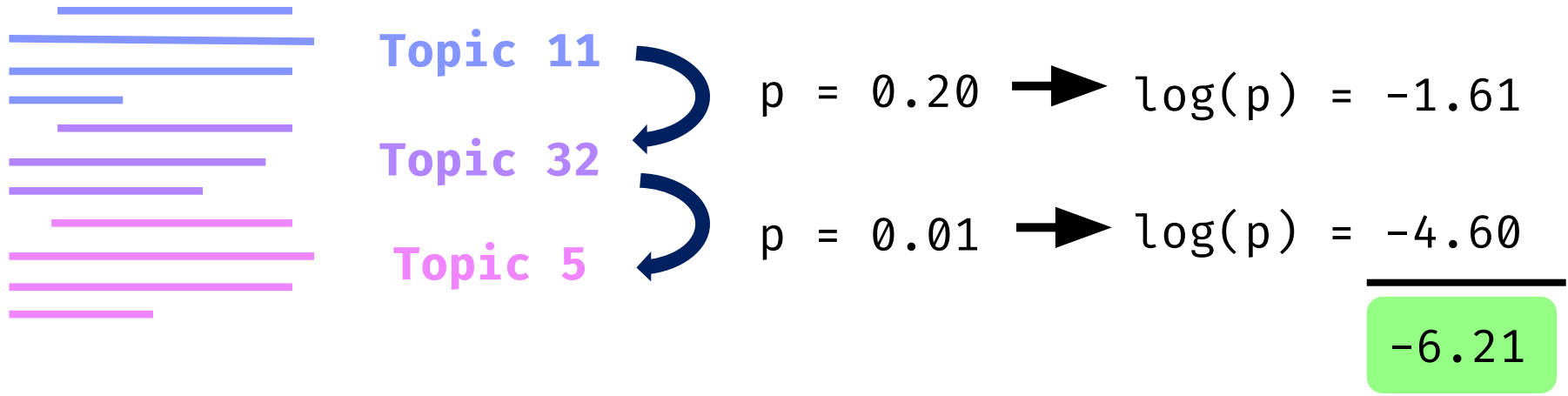
My **positive medicated** birth story



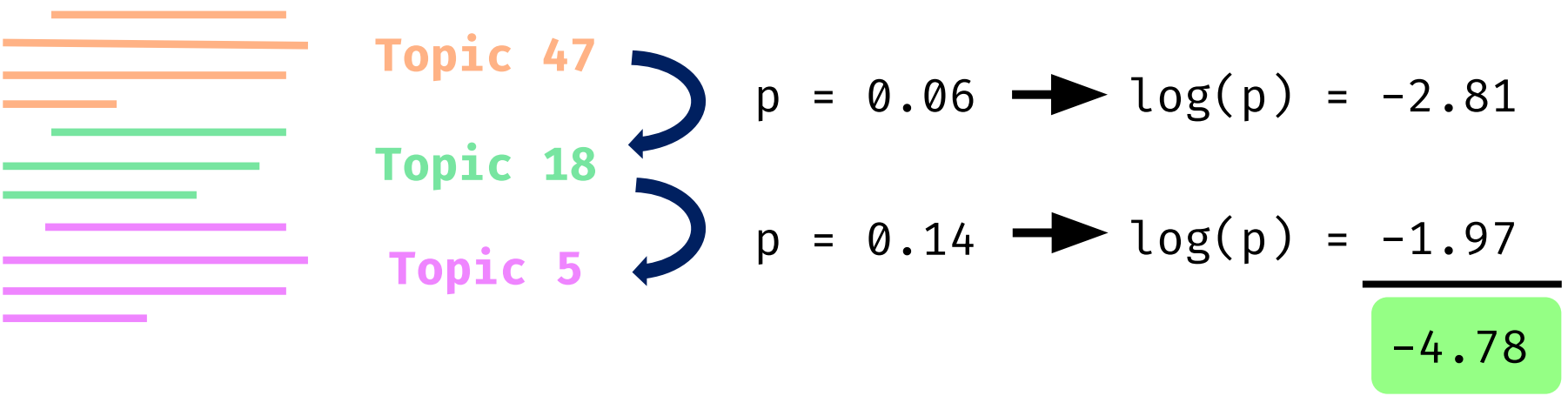
Jonah's birth story: **positive, medicated, c-section**



My **positive medicated** birth story



Jonah's birth story: **positive, medicated, c-section**



| Story Log Prob. | Bigram from Story Title | Story Log Prob. | Bigram from Story Title |
|------------------------|--------------------------------|------------------------|--------------------------------|
| -34.19 | positive medicated | -35.79 | traumatic birth |
| -34.27 | positive hospital | -35.82 | story unmedicated |
| -34.30 | med free | -35.93 | story baby |
| -34.52 | positive induction | -35.94 | post partum |
| -34.53 | story ftm | -35.95 | story plus |
| -34.73 | vaginal delivery | -35.95 | due date |
| -34.77 | story hospital | -35.99 | pp advice |
| -34.83 | weeks pp | -36.02 | baby birth |
| -34.85 | hour labor | -36.03 | home birth |
| -34.88 | super long | -36.04 | c section |
| -34.92 | failed induction | -36.05 | story warning |
| -34.95 | super positive | -36.11 | unplanned c |
| -34.95 | late birth | -36.13 | slightly traumatic |
| -35.01 | story positive | -36.27 | natural birth |
| -35.06 | hospital birth | -36.40 | belated birth |
| -35.07 | story finally | -36.42 | positive unmedicated |
| -35.07 | water birth | -36.42 | emergency c |
| -35.12 | vaginal birth | -36.53 | trigger warning |
| -35.27 | line jumper | -36.60 | induction epidural |
| -35.31 | story born | -36.84 | happy ending |

**Likely
Topic
Transitions**

**Unlikely
Topic
Transitions**

| Story Log Prob. | | Bigram from Story Title | Story Log Prob. | | Bigram from Story Title |
|---|-------------|--------------------------------|---|--------|--------------------------------|
| Likely Topic Transitions | -34.19 | positive medicated | Unlikely Topic Transitions | -35.79 | traumatic birth |
| | -34.27 | positive hospital | | -35.82 | story unmedicated |
| | -34.30 | med free | | -35.93 | story baby |
| | -34.52 | positive induction | | -35.94 | post partum |
| | -34.53 | story ftm | | -35.95 | story plus |
| | -34.73 | vaginal delivery | | -35.95 | due date |
| | -34.77 | story hospital | | -35.99 | pp advice |
| | -34.83 | weeks pp | | -36.02 | baby birth |
| | -34.85 | hour labor | | -36.03 | home birth |
| | -34.88 | super long | | -36.04 | c section |
| | -34.92 | failed induction | | -36.05 | story warning |
| | -34.95 | super positive | | -36.11 | unplanned c |
| | -34.95 | late birth | | -36.13 | slightly traumatic |
| | -35.01 | story positive | | -36.27 | natural birth |
| | -35.06 | hospital birth | | -36.40 | belated birth |
| | -35.07 | story finally | | -36.42 | positive unmedicated |
| | -35.07 | water birth | | -36.42 | emergency c |
| | -35.12 | vaginal birth | | -36.53 | trigger warning |
| -35.27 | line jumper | -36.60 | induction epidural | | |
| -35.31 | story born | -36.84 | happy ending | | |

| Story Log Prob. | | Bigram from Story Title | Story Log Prob. | | Bigram from Story Title |
|---|---------------|--------------------------------|---|--------|--------------------------------|
| Likely Topic Transitions | -34.19 | positive medicated | Unlikely Topic Transitions | -35.79 | traumatic birth |
| | -34.27 | positive hospital | | -35.82 | story unmedicated |
| | -34.30 | med free | | -35.93 | story baby |
| | -34.52 | positive induction | | -35.94 | post partum |
| | -34.53 | story ftm | | -35.95 | story plus |
| | -34.73 | vaginal delivery | | -35.95 | due date |
| | -34.77 | story hospital | | -35.99 | pp advice |
| | -34.83 | weeks pp | | -36.02 | baby birth |
| | -34.85 | hour labor | | -36.03 | home birth |
| | -34.88 | super long | | -36.04 | c section |
| | -34.92 | failed induction | | -36.05 | story warning |
| | -34.95 | super positive | | -36.11 | unplanned c |
| | -34.95 | late birth | | -36.13 | slightly traumatic |
| | -35.01 | story positive | | -36.27 | natural birth |
| | -35.06 | hospital birth | | -36.40 | belated birth |
| | -35.07 | story finally | | -36.42 | positive unmedicated |
| | -35.07 | water birth | | -36.42 | emergency c |
| -35.12 | vaginal birth | -36.53 | trigger warning | | |
| -35.27 | line jumper | -36.60 | induction epidural | | |
| -35.31 | story born | -36.84 | happy ending | | |

| Story Log Prob. | | Bigram from Story Title | Story Log Prob. | | Bigram from Story Title |
|---|---------------|--------------------------------|---|--------|--------------------------------|
| Likely Topic Transitions | -34.19 | positive medicated | Unlikely Topic Transitions | -35.79 | traumatic birth |
| | -34.27 | positive hospital | | -35.82 | story unmedicated |
| | -34.30 | med free | | -35.93 | story baby |
| | -34.52 | positive induction | | -35.94 | post partum |
| | -34.53 | story ftm | | -35.95 | story plus |
| | -34.73 | vaginal delivery | | -35.95 | due date |
| | -34.77 | story hospital | | -35.99 | pp advice |
| | -34.83 | weeks pp | | -36.02 | baby birth |
| | -34.85 | hour labor | | -36.03 | home birth |
| | -34.88 | super long | | -36.04 | c section |
| | -34.92 | failed induction | | -36.05 | story warning |
| | -34.95 | super positive | | -36.11 | unplanned c |
| | -34.95 | late birth | | -36.13 | slightly traumatic |
| | -35.01 | story positive | | -36.27 | natural birth |
| | -35.06 | hospital birth | | -36.40 | belated birth |
| | -35.07 | story finally | | -36.42 | positive unmedicated |
| | -35.07 | water birth | | -36.42 | emergency c |
| -35.12 | vaginal birth | -36.53 | trigger warning | | |
| -35.27 | line jumper | -36.60 | induction epidural | | |
| -35.31 | story born | -36.84 | happy ending | | |

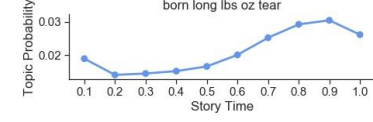
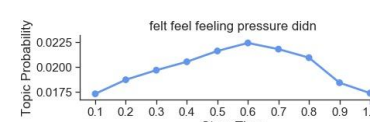
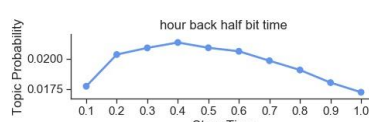
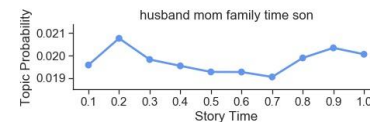
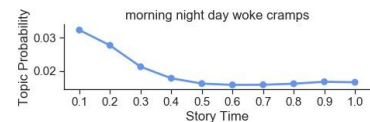
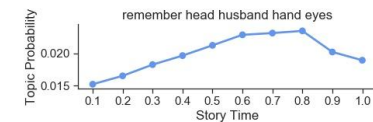
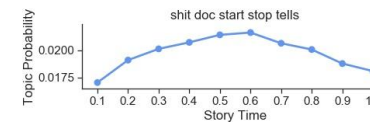
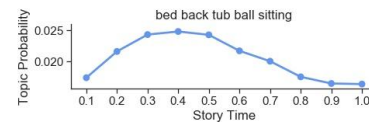
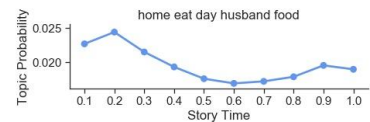
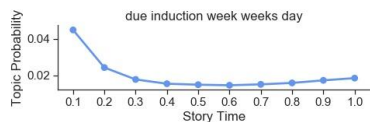
r/BabyBumps: Limitations

- Our birth stories only include “**happy endings**” with no lost pregnancies
- Skew towards **home** births and **unmedicated** births
- No explicit/verified demographic information...
- ...but the authors generally
 - write in English
 - describe experiences in the U.S., Canada, and the U.K.
 - have access to Reddit

Takeaways from birth stories

We can use computational tools to model the shared **narrative patterns** and **power framing** in a community's set of birth stories.

We discovered sets of **diverging pathways**, found **outlier** stories labeled with terms of surprisal, trauma, and **happy endings**.





Sensemaking About Contraceptive Methods Across Online Platforms

LeAnn McDowall, Maria Antoniak, David Mimno

International Conference on Web & Social Media (ICWSM), 2024



Difficult healthcare choices



Birth control plays an important role beyond contraception and can be used to treat and manage medical conditions.

But birth control methods are not one-size fits all, and the choices of whether to use birth control and which method to select are complicated by **personal beliefs, cost and accessibility**, and a wide array of **side effects** that are difficult to predict and identify.

When navigating this decision, birth control users face a **sensemaking** challenge.

Research Questions



Which birth control methods and side effects are more likely to be discussed **on different online platforms**?



What kinds of **sensemaking activities** that birth control discussants engage in online and how these differ by platform?

Data Collection: Reddit and Twitter

| Community | # of Posts | Vocab Size | Mean Tokens | Year Range | Posts Dist. (2007-2020) | Moderation | Structure |
|-----------------|------------|------------|-------------|------------|-------------------------|-----------------|------------------------|
| Reddit Posts | 68,958 | 49,088 | 79 | 2010-2020 | | user moderators | forum posts |
| Reddit Comments | 264,912 | 67,837 | 32 | 2010-2020 | | user moderators | replies to forum posts |
| Twitter Posts | 499,796 | 398,910 | 12 | 2006-2020 | | company | tweets (no retweets) |
| Twitter Replies | 211,896 | 73,896 | 12 | 2007-2020 | | company | replies to tweets |

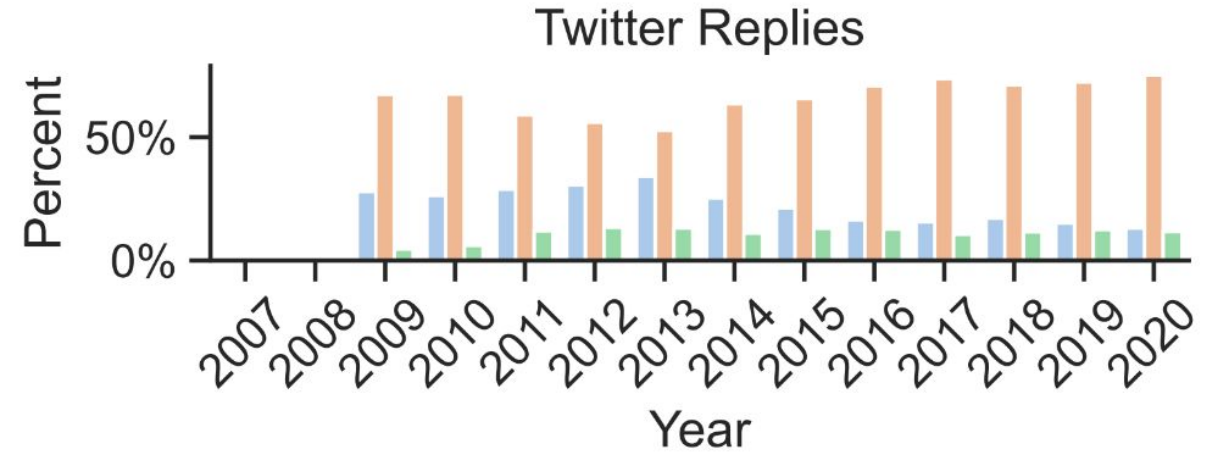
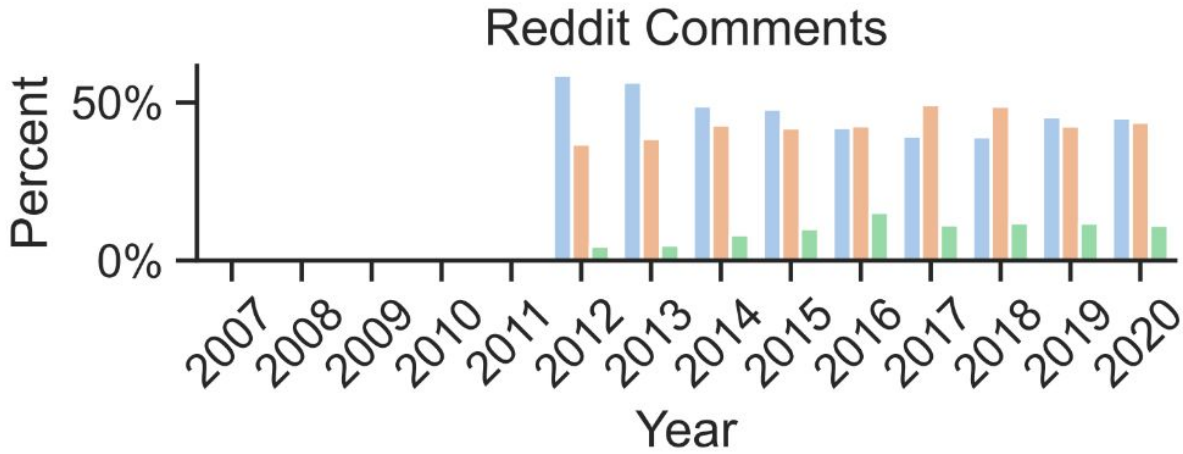
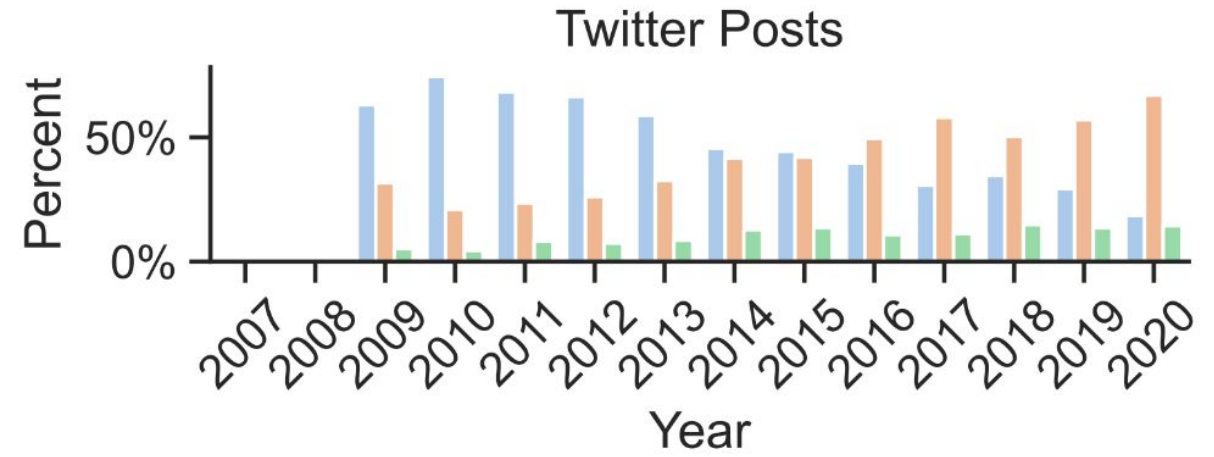
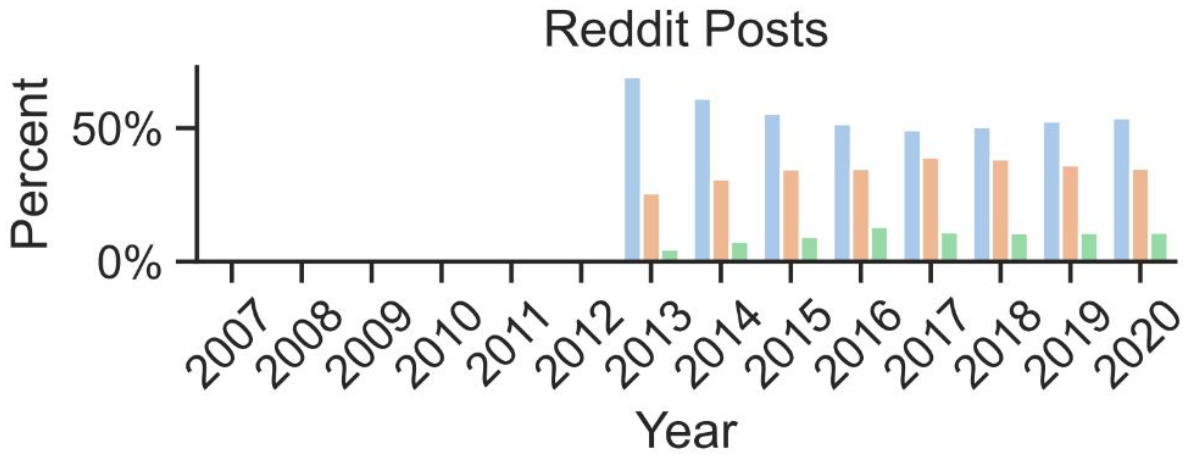
Table 1: Overview of the two datasets, including only texts mentioning our target birth control methods.

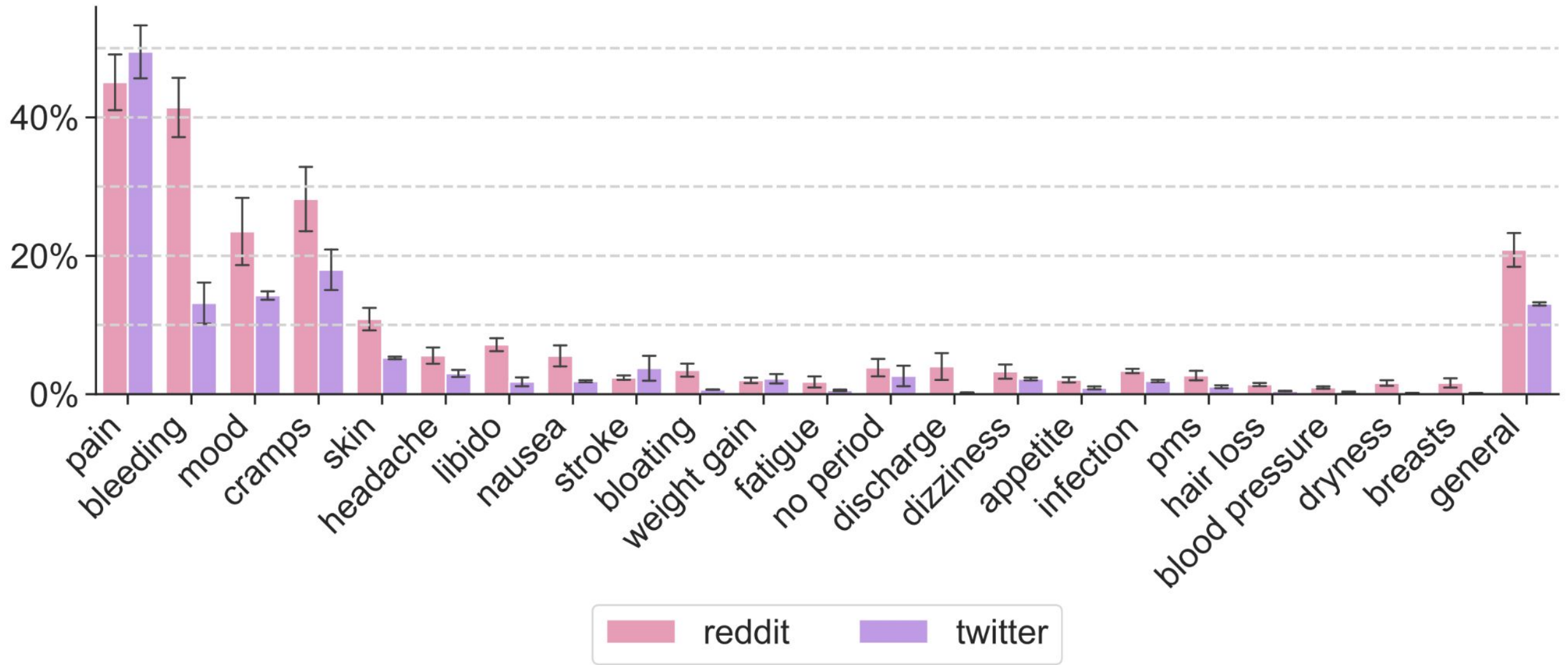
Methods

Custom Lexicon: Birth Control Methods

Custom Lexicon: Side Effects

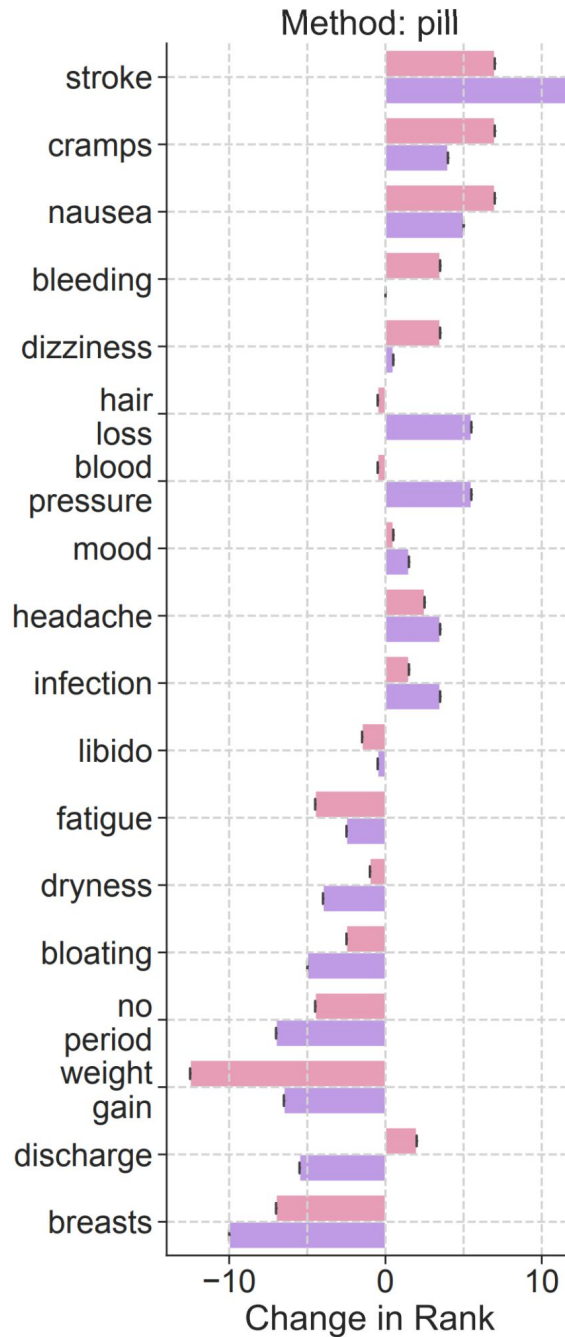
Topic Model: Latent Dirichlet Allocation (LDA)





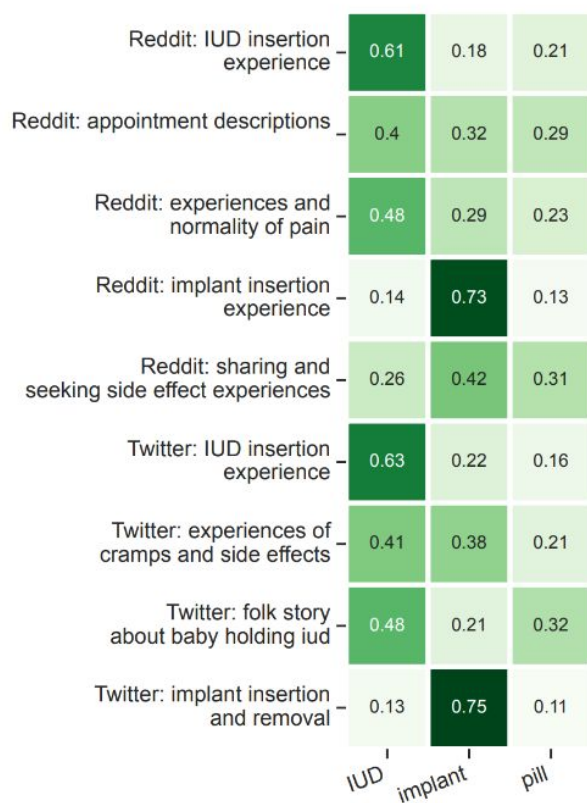
Comparison between self-reported survey data and observed frequencies on social media

←
reported more in surveys

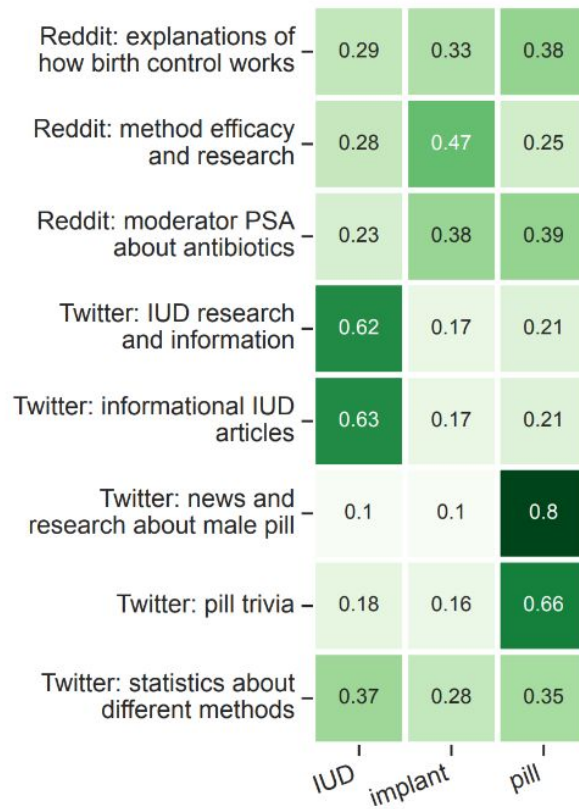


→
observed more on social media





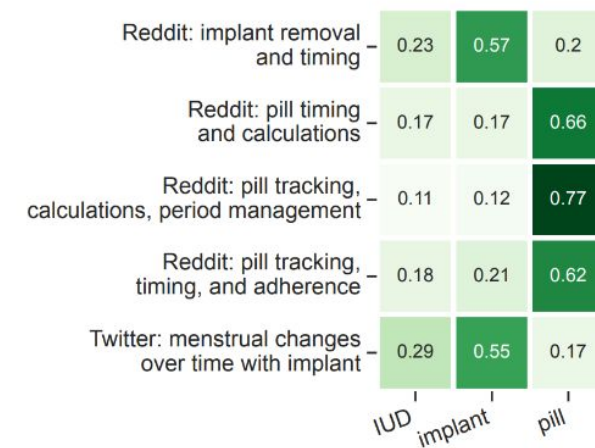
(a) Storytelling



(b) Information & Explanations



(c) Risk Analysis



(d) Timing & Calculations

Contributions

- We identify a unique combination of sensemaking strategies including storytelling, risk analysis, timing and calculations, causal reasoning, method and hormone comparison, and information and explanations.
- Across platforms, we find that storytelling is used to prepare for and overcome painful insertion experiences.
- Twitter users are more likely to discuss the IUD and severe side effects, while Reddit users frequently discuss both the IUD and the pill as well as sensitive side effects like bleeding.
- We compare our results to self-reported survey data, highlighting side effects for which Twitter and Reddit users discuss more than expected, perhaps indicating increased interest and needs met by the platforms

Future Work: Modeling Narratives



Storytelling is a powerful driver of community **sensemaking** processes that can also spread **misinformation**.

Need for more studies on new online communities like TikTok where storytelling is part of a longer **folkloric** and **memetic** tradition.

Narrative medicine to empower care seekers and motivate empathy in caregivers.

Collaborators: narratologists, NLP researchers, web & social media researchers

Future Work: LLMs and Healthcare



We need **new solutions** to inaccessibility, physician burnout, etc.

We're **already** observing care-seekers using LLMs to script communication with their healthcare providers, seek information, etc.

But there are many **risks** involved in using NLP to address those challenges: power consolidation, privacy implications, biases and errors

Future Work: Probing LLMs

Stability evaluations when using LLMs for **small, socially-specific** datasets and tasks (or in cases where “tasks” aren’t clear and data exploration is the goal).

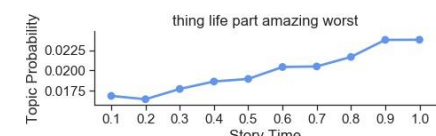
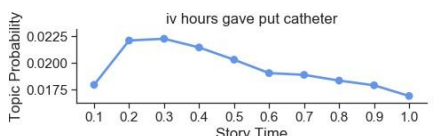
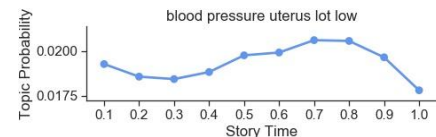
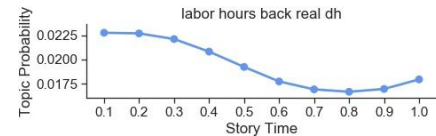
Benchmarking model performance across **domains** and **communities**:
measuring variation in and across specific **cultural contexts**.



Thank you! Questions?



maria-antoniak.github.io



FOUNDATIONS OF RESPONSIBLE NLP USE FOR MATERNAL HEALTH EQUITY

