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Analyzing the Stance of Facebook Posts on Abortion Considering State-Level Health and Social Compositions

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Abstract

Abortion remains one of the most controversial topics, especially after overturning the Roe v. Wade ruling in the United States. Previous literature showed that the illegality of abortion could have serious consequences, as women might seek unsafe pregnancy terminations, leading to increased maternal mortality rates and negative effects on their reproductive health. Therefore, the stances of the abortion-related Facebook posts were analyzed at the state level in the United States from May 4 until June 30, 2022, right after the Supreme Court's decision was disclosed. In more detail, a pre-trained Transformer architecture-based model was fine-tuned on a manually labeled training set to obtain a stance detection model suitable for the collected dataset. Afterward, we employed appropriate statistical tests to examine the relationships between public opinion regarding abortion, abortion legality, political leaning, and factors measuring the overall population's health, health knowledge, and vulnerability per state. We found that infant mortality rate, political affiliation, abortion rates, and abortion legality are associated with stances toward abortion at the state level in the US. While aligned with existing literature, these findings indicate how public opinion, laws, and women's and infants' health are related, as well as how these relationships can be demonstrated by using social media data.

Introduction

Abortion is the termination of pregnancy before the fetus reaches the viable period. Globally, about 39 abortions per thousand women take place every year, and the estimation has been constant since 1990, excluding the countries that have legalized abortion, which accounts for declination in 43% of the abortion rate in those countries (Council on Foreign Relations 2023). However, unsafe pregnancy terminations have been one of the leading causes of increased maternal mortality and morbidity (Horga, Gerdts, and Potts 2013). Global estimates from 2010 to 2014 demonstrate that 45% of all abortions are unsafe abortions (World Health Organization n.d.). In addition, the restrictive abortion laws have put a financial burden on women, due to which vulnerable groups of women cannot access quality care (Coast et al. 2021), creating larger health inequities already exacerbated by the COVID-19 pandemic. Thus, access to safe abortion is affected by numerous factors such as policies and laws related to abortion, social determinants of health (SDOH), availability of the required services, etc. (Ganatra et al. 2017). Another study found that 36% of the women lacked health insurance coverage for abortion care, and 69% had to pay out of pocket for the care they received, making financial assistance crucial for abortion services, especially among the low-income women (Jones, Upadhyay, and Weitz 2013).

Maternal mortality rate (MMR) is a relevant measure for the overall health of the population. Literature shows that black women lack access to the health care services and information required to improve their reproductive health, which leads to an increased Infant Mortality Rate (IMR) and Perinatal Mortality Rate (Maternal Health Task Force 2020). With Roe V. Wade reversed, the MMR is expected to increase (Compton and Greer 2022).

Moreover, public attitudes toward abortion are related to a variety of factors, including religion, gender, stigma, political affiliation, and socioeconomic status (Mosley et al. 2020; Patev, Hood, and Hall 2019). Recently, some questionnaires and user studies examined attitudes toward Roe v. Wade (Solon et al. 2022; Crawford et al. 2022). They found that more participants supported Roe v. Wade than opposed it, while greater knowledge about Roe v. Wade was correlated with larger support for maintaining it. In the literature, social media has also been shown as an effective tool to monitor public opinions on certain topics (Karamouzas, Mademlis, and Pitas 2022; ALDayel and Magdy 2021; Chang et al. 2023). Therefore, this study analyzes the stance of social media posts towards abortion at the state level in the US right after the Supreme Court's draft about overturning Roe v. Wade had been disclosed. Afterward, we employed appropriate statistical tests to examine the relationships between public opinion regarding abortion, abortion legality, political leaning, and factors measuring the overall population's health, health knowledge, and vulnerability per state.

Based on the literature on abortion, which will be discussed in Section Hypothesis Formulation, we define and examine the following hypotheses:

- **H1:** States with a higher maternal mortality rate express less supportive stances toward abortion.
- **H2:** States with a higher infant mortality rate express less

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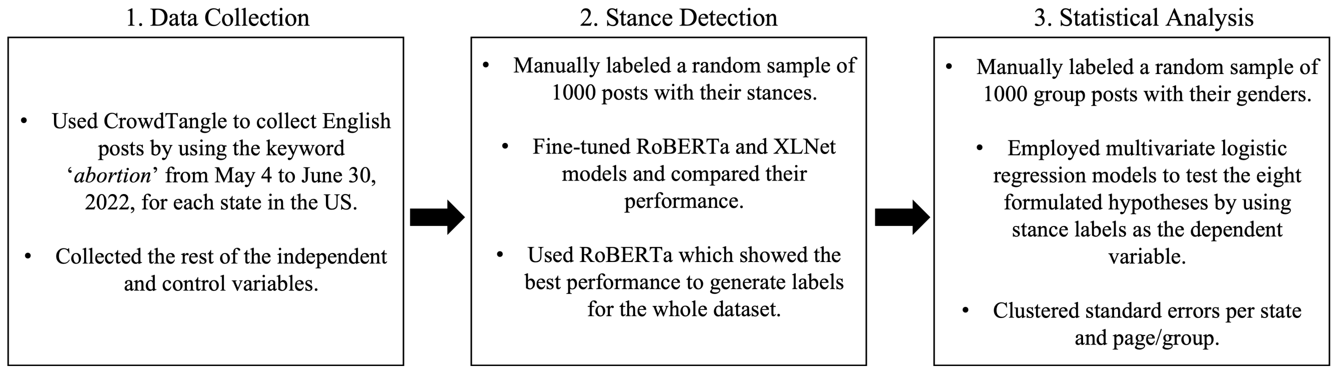


Figure 1: Study framework.

supportive stances toward abortion.

- **H3:** States that are mostly Republican express less supportive stances towards abortion.
- **H4:** States with higher rape rates express more supportive stances toward abortion.
- **H5:** States with higher social vulnerability index express less supportive stances toward abortion.
- **H6:** States with lower health literacy express less supportive stances toward abortion.
- **H7:** States with a lower number of abortions express less supportive stances toward abortion.
- **H8:** States where abortion is currently illegal express less supportive stances toward abortion.

As shown in Figure 1, we developed a framework consisting of three modules. Firstly, data were collected from one of the most widely used social media platforms, Facebook[1]. Secondly, a random sample of posts was manually labeled to obtain the ground truth dataset. Thirdly, a pretrained Transformer architecture RoBERTa model (Liu et al. 2019) was fine-tuned using the ground truth to create a well-performing stance detection model suitable for the collected dataset. Finally, multivariate regression analysis was employed to understand relationships between different factors and the stance of the posts at the state level in the US. Study findings imply that infant mortality rate, political affiliation, number of abortions, and abortion legality are significantly associated with attitudes toward abortion. In addition, we showed that there is a statistically significant difference in stances of users depending on their gender. To the best of our knowledge, this is the first study collecting and analyzing stances toward abortion expressed on social media at the *state level* in the US. Such methodology shows how natural language processing, machine learning, and social media data can be utilized to analyze public opinion around controversial topics. Also, we share the Facebook page and group unique identifiers and stick to the FAIR guidelines (FORCE11 2020), so other researchers can reproduce our dataset: https://zenodo.org/records/10904552.

[1]www.facebook.com. Accessed: 2024-04-09

Related Work

Stance detection models. Stance is defined as an individual's standpoint toward a particular topic (ALDayel and Magdy 2021). Detecting stance from their social media posts is a work in progress, and many aspects of it are still unclear (ALDayel and Magdy 2021). In more detail, stance detection refers to a process of inferring the standpoint of the writer from their text by using different features (ALDayel and Magdy 2021). A previous study discussed the orthogonal association between stance and sentiment, suggesting that, e.g., positive sentiment found in the text does not necessarily imply a supportive stance towards the topic discussed (ALDayel and Magdy 2021). As social media are common places to share viewpoints, a lot of research focuses on developing stance detection models to understand the standpoints of users about controversial topics, such as US elections (Darwish, Magdy, and Zanouda 2017; Sobhani, Inkpen, and Zhu 2017; Lai et al. 2017), and abortion (Mohammad et al. 2016; Stab et al. 2018). The performance of stance detection models employing supervised learning in recent studies slightly varies. Some approaches employing traditional machine learning models such as Support Vector Machine (SVM) achieved F1 scores of 69% (Mohammad, Sobhani, and Kiritchenko 2017) and 63.6% (Elfardy and Diab 2016), while the work leveraging a bidirectional LSTM with a fast-text embedding layer reported an F1 score of 72.1% (Siddiqua, Chy, and Aono 2019). However, recently, several studies approach stance detection by using BERT-based models (Kawintiranon and Singh 2021; Liu et al. 2021; Alturayeif, Luqman, and Ahmed 2022; Glandt et al. 2021; Clark et al. 2021; Barbieri et al. 2020) reporting average F1 scores in range approximately between 0.7 to 0.9. Prior literature found that BERT-based models outperform other models in stance detection on SemEval 2016 dataset (Ghosh et al. 2019) reaching state-of-the-art performance with accuracies close to or above 0.9 (Slovikovskaya 2019; Dulhanty et al. 2019; Liu et al. 2022).

Analysis of abortion online discussions. Previous research showed that social media might be a great tool to analyze public attitudes on different topics (Karamouzas, Mademlis, and Pitas 2022; ALDayel and Magdy 2021; Chang et al. 2023). For example, one study found that there was an increased interest in posting abortion-related tweets in the period of early May of 2023, before the official overturning of Roe v. Wade (Mane et al. 2022). Another study investigated emotions around controversial topics on online debate forums (Li and Xiao 2020). Their findings suggest that abortion discussions contained the highest number of comments expressing an emotion of disgust compared to other emotions. Also, previous research found that gender and political affiliation were associated with the use of incivility and intolerance in abortion referendum Twitter discussions (Oh et al. 2021). Finally, there are certain publicly available datasets that include abortion-related posts (Mohammad et al. 2016; Stab et al. 2018; Chang et al. 2023).

However, to the best of our knowledge, none of the studies investigated the public stance toward abortion at the state level and the factors associated with it, making our dataset novel compared to previous works.

Data Collection

People tend to discuss matters such as political issues and abortion on social media (Karamouzas, Mademlis, and Pitas 2022; ALDayel and Magdy 2021; Chang et al. 2023; Li and Xiao 2020). Furthermore, Facebook still remains one of the most utilized platforms (Pew Research Center 2021). Therefore, the data have been collected from Facebook by using CrowdTangle (CrowdTangle Team 2022), a social media insights tool that provides data from highly influential public pages, groups, and verified users. Note that CrowdTangle does not allow data to be collected from personal and private accounts or posts visible only to specific users. However, CrowdTangle lets users search the posts based on filters such as local relevance, time frame, language, keywords, etc. It is important to note that CrowdTangle finds the locations of pages/groups based on the geographic distribution of their followers on Facebook. Therefore, the English posts that contained the keyword ‘abortion’ were collected for each state in the US from May 4 to June 30, 2022, after the leak of the Supreme Court’s decision to overturn Roe V. Wade. The total number of posts collected was 82,056 from 13,946 unique public pages and 13,923 posts from 2,822 unique public groups. Note that Facebook *public pages* and *public groups* are different. According to Facebook, public pages are suitable for artists, public figures, businesses, etc., to reach their audience (Facebook n.d.). On the other hand, groups are usually places where people of similar interests connect and share their thoughts (Facebook n.d.). Therefore, posts of a *page* are shared by page admin(s) with no way for us to identify them, while posts from *groups* are shared by the members of the group whose Facebook accounts might be identifiable.

As indicated in Figure 2, certain states contain more Facebook posts collected compared to others. While some states have more posts than others, we could obtain enough posts for all the states, with the most amount of posts being from California (8,183 posts) and Texas (6,122 posts), and the least amount of posts being from Alaska (438 posts) and Hawaii (428 posts).

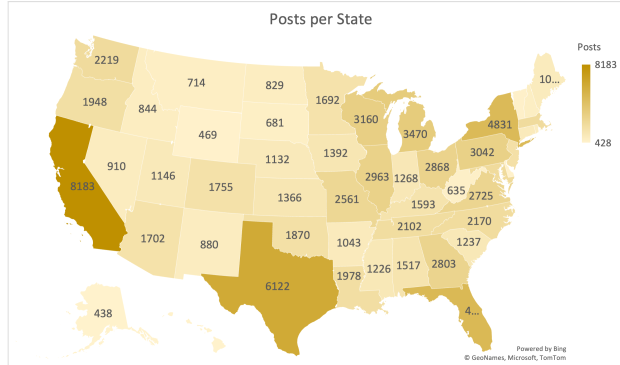


Figure 2: Number of posts per state.

Stance Detection

To detect the stance of Facebook posts about abortion, we developed a model using a transfer learning approach, using XLNet (Yang et al. 2019) and RoBERTa (Liu et al. 2019) and fine-tuning them on a ground truth dataset. While deep learning models have been used for stance detection on other topics, such as political debates (Kawintiranon and Singh 2021; Liu et al. 2022), or COVID-19 issues (Glandt et al. 2021), to the best of our knowledge, this work is the first to develop an abortion stance detection model.

Stance detection models: As discussed in the Related Work Section, the previous literature shows that BERT-based models achieve current state-of-the-art performance. Thus, XLNet (Yang et al. 2019) (specifically, the *xlnet-base-cased* variant) and RoBERTa (Liu et al. 2019) (specifically, the *roberta-base* variant) models were fine-tuned on the 1,000 labeled posts to create the stance detection model. Both are large language models based on the Transformer architecture (Vaswani et al. 2017), and both models regularly achieve very high accuracy on many prediction tasks. While there are studies employing XLNet (SU et al. 2021; Yang et al. 2019), previous research suggests that RoBERTa can achieve state-of-the-art results outperforming BERT and XLNet (Slovikovskaya 2019; Dulhanty et al. 2019; Liu et al. 2022; Barbieri et al. 2020). Despite its strong performance, RoBERTa has a maximum input length when processing texts. However, the number of posts longer than RoBERTa’s maximum length in the dataset was only 1.9%, thus making using RoBERTa still possible. XLNet has no such limitation and was included as a candidate model due to the potentially uncapped length of Facebook posts.

Groundtruth creation: Firstly, a random sample of 1000 posts was extracted and manually labeled by three coders. The data was labeled by assigning one of the following labels to each post: stance supporting abortion, stance against abortion, and no stance. After the manual labeling by annotators was completed, the final labels for each post were determined if at least two coders assigned the same label to the same post. However, in 47 posts, labels assigned by three coders were different. Thus, the annotators discussed and agreed on the final labels for such posts. In addition, we calculated a Fleiss’ Kappa (Fleiss, Levin, and Paik

2013) to better understand the inter-rater agreement. The obtained value equals 0.424, representing moderate agreement (Fleiss, Levin, and Paik 2013). This implies that abortion stance detection is a hard task even for humans; making implementation of a well-performing stance detection model even harder. Afterward, we used this ground truth dataset to train and test stance detection models. The resulting dataset was heavily imbalanced in favor of "no stance" (N=470) and "supporting" (N=431); "against" stances only accounted for 99 of the messages. The next section discusses the techniques used to mitigate the effects of this imbalance.

The dataset was split into a training, testing, and validation fold, using 80% of the data for training, 10% for validation, and 10% for testing. The folds were selected at random and stratified on the stance labels. The training has been performed on an NVIDIA P100 GPU with 16 GB of VRAM. Both models were fine-tuned using the AdamW optimizer with a learning rate of 10^{-5} and a training batch size of 4. Early stopping was used to terminate training once the macro F1 score on the validation dataset failed to decrease for 5 training epochs, at which point the best-performing model weights were restored and evaluated on the test set. To address the issue of data imbalance, a weighted cross-entropy loss was used (Aurelio et al. 2019). Cross-entropy is calculated as normal, but the per-class loss is scaled by a factor of $\frac{1}{N}$, where N is the total number of training observations in that class, i.e., the final loss function takes the form:

$$\ell(y, \hat{y}) = -\sum_{i=0}^{C} \frac{1}{N_i} log \frac{exp(\hat{y}_i)}{\sum_{j=0}^{C} \hat{y}_j} y_i$$

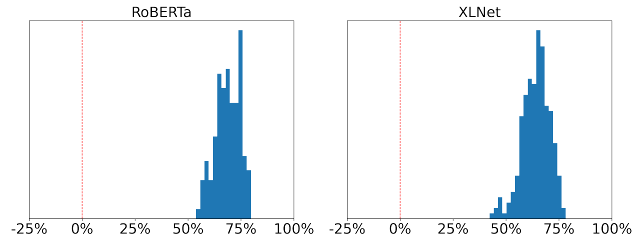
Where $\hat{y}_i$ is the model's raw (i.e. logit) prediction for class i, y_i is the ground truth value for class i (either 0 or 1), and N_i is the number of training examples in class i.

Due to the small size of the training dataset, the above training process was repeated 250 times to obtain a more robust measurement of the models' performance. Different training-validation-testing splits may result in markedly different model performances depending on which observations end up in which split. Repeating the training procedure multiple times is intended to measure the empirical distribution of model performance under different possible splits. After the 250 training rounds were completed, the average stopping epoch (i.e., the training epoch where the model obtained the best performance on the validation sets) was calculated and used to re-train the final model on the entire training dataset. Table 1 shows the summary of model performances, averaged across the 250 training runs.

Model	Macro F1	Balanced Accuracy
RoBERTa	69.01 (5.95)	69.24 (6.43)
XLNet	64.18 (6.50)	63.72 (6.52)

Table 1: Model performances across 250 random training-validation-testing splits. Stds are in parentheses.

Figure 3 shows a histogram of the performance metrics' distributions. RoBERTa shows higher performance than XLNet, with an average F1 of 69.01 versus XLNet's 64.18 and a balanced accuracy score of 69.24 versus XLNet's 63.72. While these performance metrics are not competitive with the state-of-the-art stance detection models, it is important to note that the inter-rater agreement of Fleiss' Kappa being 0.424 shows how hard it is even for three human annotators to agree on the stance of the posts. Thus, looking for a high-performance stance detection model trained on such a dataset might be an impossible expectation.



(a) (b)

Figure 3: Distributions of model scores across 250 training rounds for RoBERTa and XLNet (3a and 3b). A vertical reference line is at 0%.

Detecting stance of all posts: Since the RoBERTa model obtained the highest average performance, it was selected as the final model to re-train over the entire training dataset. Following these results, a RoBERTa-base model was fine-tuned over the entire 1,000 post dataset for 5 epochs. The fine-tuned model was then used to generate predictions for the remaining posts.

The following attributes were obtained for each post in the dataset: LABEL_FOR, LABEL_AGAINST, and LABEL_NO_STANCE, which add up to 1, where each provides a likelihood of the post containing this stance about abortion. To better understand the distribution of posts' stances in our dataset, a ternary graph was plotted by using a random sample of 1000 posts and their scores (Figure 4). It is clear that the lowest portion of posts is against abortion, while larger numbers of posts are supporting abortion or neither. Finally, to label each post with its stance, the highest value of three scores was picked. Therefore, each post had a *stance* of being for, against, or neutral towards abortion. The number of posts being pro-life is 26,999, while the number of posts being pro-choice is 30,042. We found 38,938 posts that did not express a stance toward abortion. Inaccurate stance detection could impact our hypothesis testing findings. To minimize this impact, we only used the labels with high confidence and discarded those labeled as *no stance*.

Hypothesis Formulation

In this study, we use stance towards abortion as the dependent variable, as it aims to closely investigate relationships among SDOH and other factors that might affect abortion rates at the state level in the US and the stance expressed in Facebook posts originating from those states.

The distributions of supporting and opposing stances in US states are shown in Figures 5a and 5b. Note that posts

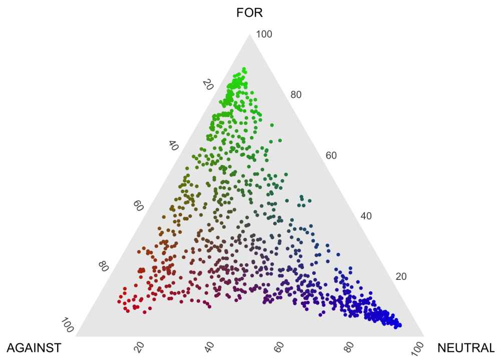


Figure 4: Scores of a random sample of posts.

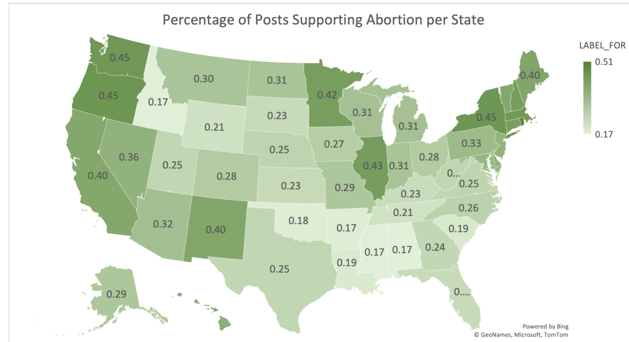
that express no stance are discarded from the analysis. As indicated, the distribution of stances per state is quite different. For example, the state with the highest percentage of posts against abortion is Arkansas, while the state with the highest percentage of posts supporting abortion is Rhode Island, followed by Oregon. Therefore, it is crucial to understand such differences in attitudes toward abortion among US states.

Maternal Mortality Rate (MMR) refers to the number of maternal deaths per 100,000 live births (Centers for Disease Control and Prevention 2022b). A study by Addante et al. found that states with more abortion restrictions had higher MMR, even after controlling for factors such as race, income, and healthcare access. Specifically, the MMR was increased by 10% for every additional abortion restriction in a state. Therefore, greater economic and social gaps may be reflected in increased MMR, which may also have an impact on views toward abortion as well as accessibility to reproductive healthcare. Therefore, we defined the first hypothesis and used MMR as an independent variable. *H1: States with a higher MMR express less supportive stances toward abortion* We extracted the MMR in the US from 2018 to 2020 from the CDC (Centers for Disease Control and Prevention 2023a). Note this study employs the numeric variable *Deaths* from this dataset without missing values.

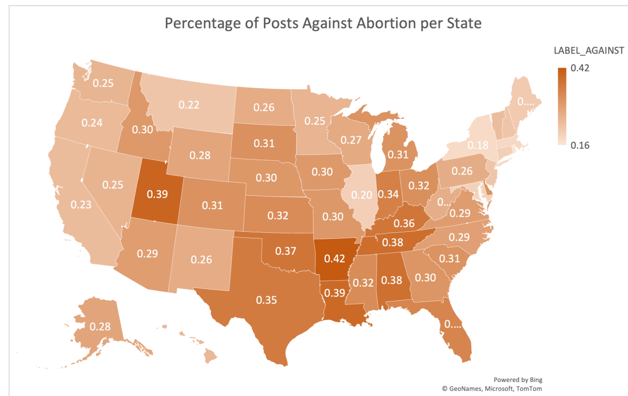
Infant Mortality Rate (IMR) is the number of deaths of infants under the age of one per 1,000 live births in a given population (Centers for Disease Control and Prevention 2022a). Newborns who were given birth in states with stricter abortion laws had a higher risk of infant death than those who were given birth in states with no such restrictions (Pabayo et al. 2020). Also, prior studies noted a decline in the IMR over 3 years in certain states after the legalization of abortion in 1970 in three out of five income classes (Krieger et al. 2015). Therefore, based on the literature, we defined the second hypothesis and used IMR as a numeric independent variable: *H2: States with a higher IMR express less supportive stances toward abortion*. We obtained IMR rates in 2020 from Statista Research Department (Statista Research Department 2022b).

Political Affiliation. Prior studies showed that Republicans were more inclined to support overturning Roe v. Wade, whereas the Democrats had a greater likelihood to support maintaining Roe v. Wade (Crawford et al. 2022). In addition, a report from Ipsos shows that 56% of Republicans are seemingly against the legalization of abortion while 81% of Democrats support it (Ipsos 2023). Multiple methods can be used for determining the political affiliation of a state, such as their governor affiliation, senate majority, house majority, attorney general, etc. Some recent studies employed the affiliation of the governor (Neelon et al. 2021). Therefore, we also determined the political affiliation at the state level by the political affiliation of the state governor, and it was used as a categorical independent variable to test the third hypothesis: *H3: States that are mostly Republican express less supportive stances towards abortion*. The data on state political affiliation were obtained from KFF (The independent source for health policy research, polling, and news 2023).

Rape Rate was obtained per 100,000 inhabitants in 2020 at the state level in US (Statista Research Department 2022a) and was used as an independent variable in the analysis. Existing legal hurdles in many cases restricted access to abortion services by pregnant rape victims (Bhate-Deosthali and Rege 2019). A study conducted to investigate the cause associated with which women opt to undergo an abortion revealed that 1% of the total subjects had been victims (Finer et al. 2005). Many factors contribute to a raped woman un-



(a)



(b)

Figure 5: The distribution of abortion supporting and opposing stances at the state level in the US.

dergoing a denial process that restricts their access to obtaining abortion services, which in turn is made even worse by the complicated legal system that is currently prevalent (Lara et al. 2006). Thus, the fourth hypothesis is as follows: *H4: States with higher rape rates express more supportive stances toward abortion.*

Social Vulnerability Index (SVI) considers factors like income, education, housing, access to transportation, access to healthcare, etc., and measures how vulnerable populations' health might be if experiencing external stressors (Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry/ Geospatial Research, Analysis, and Services Program 2018). A qualitative study (Ouédraogo and Sundby 2014) concluded that the factors that contribute to limited access to safe abortion are a poor financial background, a lack of education, ignorance of reproductive health, cultural and religious beliefs, and the legal system. Additionally, the rate of unintended pregnancy has been decreasing, but it has been seen in a higher ratio among women with lower socioeconomic status (Finer and Zolna 2016). As a result, SVI barriers might have an impact on accessing reproductive healthcare as well as attitudes toward abortion. The SVI data were obtained from the CDC/ATSDR SVI database the CDC/ATSDR SVI database (Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry/ Geospatial Research, Analysis, and Services Program 2018). However, the SVI scores provided are at the US county level. Therefore, the SVI scores in this study represent a weighted average of state counties' SVI scores given their population as weights, and they were used as a numeric independent variable in the analysis. As SVI is shown as one of the factors that contribute to limited access to safe abortion, states with higher SVI might experience lower abortion rates as well as restricted abortion laws. Thus, the following hypothesis has been developed: *H5: States with higher SVI express less supportive stances toward abortion.*

Health Literacy (HL) refers to an individual's capability to locate, comprehend, and apply the information needed to make essential decisions concerning their health (Centers for Disease Control and Prevention 2023b). A Texas study that looked at women's knowledge, opinions, and experiences with self-induction methods for abortion revealed that many of them had heard of them, had favorable opinions of them, and that only a small percentage of them had tried them (Grossman et al. 2015). According to the study, to decrease the prevalence of unsafe abortion practices, reliable and easily accessible information regarding safe and legal abortion services is required (Grossman et al. 2015). This shows that HL has a humongous impact on how people perceive abortion policy. Finally, HL data were gathered from The University of North Carolina at Chapel Hill (National Health Literacy Mapping to Inform Health Care Policy 2014) by utilizing information from the census blocks of 2010. Note that the HL data obtained is at the census block level. Therefore, a numeric independent variable at the state level is a weighted average of provided HL scores given census group population as weights. We hypothesize that higher HL might lead to higher awareness about reproductive healthcare and its accessibility, leading to higher abortion rates in such states. This being the case, we will test the following hypothesis: *H6: States with lower health literacy express less supportive stances toward abortion.*

Number of Abortions is affected by the restrictive abortion laws and accessibility of abortion care, whereas the per capita income, the percentage of believers in Catholicism, and the proportion of individuals raised across the state have an indirect impact on the rates of abortion (Gober 1997). The abortion rate decreased from 1.61M to 1.31M in the year 1990-2000, and around the same year, the number of abortion service providers decreased by about 38%, these figures demonstrate that the availability of the services impacts abortion rates patterns (Finer and Henshaw 2003). The data for the number of abortions in the US states was retrieved from the Guttmacher Institute (Guttmacher Institute 2023), and it has been used as a numeric independent variable in the regression model. Therefore, we hypothesize that states where a higher number of abortions occur practice protective abortion laws and, thus, more supporting attitudes toward abortion: *H7: States with a lower number of abortions express less supportive stances toward abortion.*

Abortion Legality is the legality of abortion in a particular state. Women may seek unsafe abortions in nations where abortion is controlled, which can have fatal consequences. In contrast, women may have more control over their reproductive health in nations where abortion is accessible and are less likely to suffer from adverse health effects associated with unexpected pregnancies. According to a prior study (Finer and Fine 2013), stringent abortion laws may potentially harm the health of mothers in many ways. Therefore, we hypothesize that the states with protective abortion laws experience a higher number of abortions, leading to lower MMR: *H8: States where abortion is currently illegal express less supportive stances toward abortion.*

Information on state-level abortion regulations in the US after the Dobbs v. Jackson ruling was gathered from the Guttmacher Institute (Guttmacher Institute 2023). We used the new state-specific legal status on May 4, 2023, even though states did not modify their laws simultaneously because modification of laws has been a continuous conversation for a long time and mostly anticipated. Therefore, the new abortion laws could not significantly change the attitudes of the state population toward abortion. In this map, abortion legality comprises the following labels (Guttmacher Institute 2023), which were used as a categorical independent variable in the analysis: *Most restrictive* is defined as cases when states fully ban abortion. *Very restrictive* is defined as states having numerous restrictions and early gestational age ban. *Restrictive* is defined as states having numerous restrictions and later gestational age bans. *Some restrictions/protections* is defined as states either have a couple of restrictions/protections or a combination of them. *Protective* is defined as states employing some protective policies. *Very protective* is defined as states employing most of the protective policies. *Most protective* is defined as states employing all or most of the protective policies.

Religiousness is an individual's faith, dedication, and regard towards anything divine (Gallagher and Tierney 2013).

According to previous literature, religiousness and abortion share a close connection (Frohwirth, Coleman, and Moore 2018). The ideologies infused by religiosity and its magnitude in public and socio-political belief have always induced a hesitance toward the concept of abortion and a tendency to endorse a ban on abortion except for the cases where the pregnancy is due to rape, incest or there exists a threat to the life of the mother (Ellison, Echevarria, and Smith 2005). The religiousness data were obtained from the Pew Research Center 2016 per state level in the United States (Lipka, Michael and Wormald, Benjamin 2016) and has been used as a control variable in the analysis.

Pregnancy Rate, Abortion, and Women's Age Group. According to CDC (Kortsmit 2021), some age groups have higher abortion rates than others, with the age group 20 to 24 having the greatest abortion rate. Therefore, we used the pregnancy rate for this age group per state as a control variable in statistical models. The state-level data for the pregnancy rate according to different age groups were retrieved from the Guttmacher Institute (Maddow-Zimet, Isaac and Kost, Kathryn 2021).

Pregnancy Checkups. Pregnancy checkups are shown to contribute to healthier pregnancies and childbirth (Kassaw et al. 2020). They provide confidence to pregnant mothers about the health of unborn children, which might also contribute to their decision on abortion. In a previous study, 92% of women in the first 20 weeks of gestation supported the availability of an abortion option, with 50% of them willing to consider it only during the first trimester. Among women who opt for abortion in their first or second trimester, 76% admitted to undergoing abortion after knowing that the fetus had Down syndrome, while 84% admitted that they would do so if they were exposed to a life-threatening condition or after an incident of rape or incest pregnancy (Finer and Zolna 2011). Therefore, the number of pregnancy checkups in the first trimester has been used as a control variable. The prenatal care data for pregnant women according to the state of residence was obtained from the Centers for Disease Control and Prevention (Osterman and Martin 2018).

Population of each state for 2022 was obtained from US Census Bureau (United States Census Bureau 2023) and used to normalize the number of abortions per state.

Gender is considered as a significant factor contributing to attitudes toward abortion (Patev, Hood, and Hall 2019) as a previous study found that females are more supportive of abortion than males (Loll and Hall 2019). Therefore, we extracted a random sample of 20 posts belonging to each state from the *public group* dataset to be manually checked for gender identification. Three states did not contain 20 posts expressing for or against stance; therefore, we extracted as many posts as possible from them. These states are New Jersey (16 posts), New Mexico (18 posts), New York (15 posts), North Dakota (4 posts), and Wyoming (9 posts). Thus, the dataset being labeled contained 962 posts.

Two coders manually labeled each post into either *male, female, not available,* or *unknown*. The label *not available* shows that the post no longer exists, while the *unknown* label was used when it was not possible to infer the gender. While labeling, coders visited these accounts' public profiles, checking their names, photos, and posts. People might present their gender differently on social media, so our gender analysis is limited to the accounts' perceived gender. To assess the inter-coder reliability between two coders, we performed a Cohen-Kappa test (McHugh 2012), obtaining an inter-rater agreement of 0.9, which shows almost perfect agreement. Coders resolved any conflicts in the labeling process and identified 331 females, 519 males, 43 not available posts, and 69 with unknown genders.

Descriptive Statistics

This section provides descriptive statistics on variables used in the study. Table 2 presents the minimum, median, mean, and maximum values for continuous variables.

Statistics	Min	Median	Mean	Max
# Abortions	100	$7.6K$	$18.4K$	$154K$
MMR	1	31.5	45.32	257
IMR	0	5.47	5.37	8.27
Rape Rate	14.4	39.85	43.71	154.8
SVI	0.14	0.45	0.47	0.77
HL	235.9	248	247.2	256.3
Population	$581K$	$4.6M$	$6.7M$	$39M$
Religiousness	33	54	54.7	77
Pregn. Rate	61.50	113.45	110.34	145.90
# Checkups	67	77.60	78.03	89.80

Table 2: Descriptive statistic on numeric variables.

The variables presented in Table 2 highly vary by state. For example, the minimum MMR of 1 is found in Vermont, while its maximum value of 257 is found in Texas. The mean rape rate reported is 43.71, while Alaska shows a much higher rape rate than the national average (154.8). Interestingly, the highest SVI value is 0.77 for New Mexico, which is a state with the lowest HL in the US. The top six states with the highest IMR (Mississippi, Louisiana, West Virginia, Arkansas, Alabama, and South Dakota) are 6 out of 13 states with the Most Restrictive law toward abortion.

Table 3 shows that there are 24 Democrat and 26 Republican states in our dataset. Furthermore, the number of restrictive states, very restrictive, and most restrictive toward abortion is 11, 2, and 13, respectively. On the other hand, the number of states that are protective, very protective, and most protective is 10, 5, and 1, while there are 8 states with some restrictions/protections. To better understand the relationship between categorical state variables, we show the number of posts per state category in Table 3. The number of posts that support abortion in Democrat states is higher compared to the number of posts against abortion (19,439 vs. 13,184). However, the number of posts opposing abortion is higher than those supporting abortion in Republican states (13,815 vs. 10,603). States that are most protective, very protective, protective, or employ some restrictions/protections contain a larger number of pro-choice posts compared to pro-life posts. The opposite trend is discovered in restrictive, very restrictive, and most restrictive states.

Gender manual labeling yielded 331 posts shared by accounts perceived as females and 519 posts shared by accounts perceived as males. Posts labeled by *not available* and *unknown* were removed from the analysis, lowering

Political Affiliations	# States	Supportive Posts	Opposing Posts
Democrat	24	60%	40%
Republican	26	43%	57%

Abortion Legality	# States	Supportive Posts	Opposing Posts
Most Protective	1	66%	34%
Very Protective	5	65%	35%
Protective	10	64%	36%
Some Protections	8	54%	46%
Restrictive	11	47%	53%
Very Restrictive	2	48%	52%
Most Restrictive	13	39%	61%

Table 3: Number of posts per each state category.

the number of posts to 850 published by 592 unique users. Perceived male accounts shared 382 (74%) posts against and 137 (26%) posts supporting abortion, while perceived female accounts shared 187 (56%) posts against and 144 (44%) posts supporting abortion.

Analysis and Results

Multivariate regression analysis was leveraged to test the formulated hypotheses. Each Facebook post contained the following information: *stance* (supporting or opposing abortion), state the post is associated with, number of abortions, HL, SVI, IMR, MMR, rape rate, political affiliation, religiousness, number of pregnancy checkups, and pregnant rate at age group 20-24, and legality of abortion in the state post is associated with. Firstly, we tested for multicollinearity by computing variance inflation factors (VIF). In case VIF is greater than 5 for some predictors, it indicates that these predictors are highly correlated and can cause issues in the models (Gareth et al. 2013). We calculated VIFs for all the predictor variables used in this study. VIFs found for IMR, SVI, HL, and abortion legality were 5.3, 9.7, 12.8, and 48.4, respectively, suggesting that they should not be used in the same model. Therefore, HL and the number of abortions were placed into a separate model with religiousness, pregnancy checkups, and pregnancy rate as control variables. Another model included SVI, IMR, MMR, rape rate, and political affiliation as independent variables and included all the mentioned control variables. The final model only included abortion legality as the independent variable, along with the control variables. Once again, we ran a multicollinearity test, which did not show any additional issues.

Hypotheses Testing. Analysis included three logistic regression models where standard errors were clustered per state, as there was value repetition for state-level variables. Besides, at the state level, standard errors were also clustered by the unique Facebook ID of each page/group, as the majority of unique pages/groups contained more than one post about abortion. Thus, posts shared on the same page/group might not be completely independent of each other.

For the analysis, we merged the dataset obtained from public pages with a dataset collected from public groups. Therefore, the final dataset consists of 95,979 posts. Note that posts containing the stance category LABEL_NO_STANCE were discarded, reducing the number of posts from 95,979 to 57,041. Model 1 (M1) tested hypotheses H1-H5, by examining the relationship between SVI, IMR, MMR, rape rate, and political affiliation, with *stance* as the dependent variable. Model 2 (M2) investigated the associations between HL and the number of abortions with the stance as the dependent variable, testing H6-H7. The third model (M3) tested the hypothesis H8. All models included pregnancy checkups and the pregnancy rate of women ages between 20 and 24 as control variables, while model M2 also included religiousness. The number of abortions has been divided by the total state population. Finally, due to using multiple tests to examine the hypotheses, Bonferroni correction (Bland and Altman 1995) was applied where an original p-value of 0.05 has been divided by the total number of hypotheses. Therefore, the variables that show a p-value lower than 0.006 will be considered statistically significant.

Testing H1-H5. As indicated in Table 4, the independent variables included in the model were SVI, IMR, MMR, rape rate, and political affiliation. Results suggest a significant correlation between IMR ($p < 0.0001$) and political affiliation ($p < 0.001$) with standpoints of posts regarding abortion. In more detail, a higher IMR per state is associated with a lower likelihood of pro-choice Facebook posts in such states, supporting H2. Furthermore, states being predominantly Republican decreases the likelihood of abortion-supporting posts being shared in these states, supporting H3. However, MMR, the rape rate, and SVI were not statistically significant, rejecting H1, H4, and H5. Not expressing opinions regarding rape victims or a lower percentage of abortions due to rape crimes might contribute to this attribute not being a significant indicator of abortion stance. In addition, states with elevated SVI might be more vulnerable to external stressors, but it is not the most impactful factor when it comes to abortion stances. The top 10 states with the lowest IMR (Vermont, California, Massachusetts, New York, New Jersey, Minnesota, Oregon, Rhode Island, Washington, and Connecticut) are states that are predominantly Democrat and express a higher percentage of posts supporting abortion.

Testing H6-H7. As demonstrated in Table 4, new independent variables included in the model were HL and the number of abortions. Model results show that there is a significant positive association between the number of abortions and the viewpoint of abortion-related Facebook posts in US states ($p < 0.0001$). In other words, a higher number of abortions is increasing the likelihood of Facebook posts being supportive of abortion, supporting H7. Interestingly, in the top 11 states with the highest number of abortions, only 1 state is Republican (Georgia), suggesting that such states contain a larger percentage of posts being supportive of abortion. In contrast, HL did not show statistical significance ($p > 0.006$), rejecting H6. Furthermore, the model suggests a statistically significant relationship between religiousness and stance ($p < 0.0001$). A higher percentage of the state population being highly religious is associated with a lower likelihood of sharing pro-choice posts in such states.

Testing H8. As demonstrated in Table 4, the independent variable included in the model was the legality of abortion in US states. Model results suggest that there is a significant as-

Positive class: posts supporting abortion	M1 (H1-H5)	M2 (H6-H7)	M3 (H8)
Social Vulnerability Index	-0.26 (0.45)		
Rape Rate	-0.003 (0.003)		
Infant Mortality Rate	-0.21 (0.05)***		
Maternal Mortality Rate	-0.0 (0.001)		
Political affiliation (Republican)	-0.41 (0.11)**		
Pregnancy Checkups	0.001 (0.009)	-0.003 (0.01)	-0.01 (0.01)
Pregnancy Rate in age group 20-24	-0.003 (0.005)	-0.007 (0.003)	-0.01 (0.003)***
Health Literacy		0.002 (0.01)	
# Abortions		144.14 (34.8)***	
Religion		-0.03 (0.01)***	
Legality (Most Restrictive)			-0.79 (0.11)***
Legality (Protective)			-0.06 (0.1)
Legality (Restrictive)			-0.65 (0.07)***
Legality (Some Restrictions/Protections)			-0.35 (0.15)
Legality (Very Protective)			0.13 (0.12)
Legality (Very Restrictive)			-0.49 (0.09)***
Null Deviance	78913 on 57040 df	78913 on 57040 df	78913 on 57040 df
Residual Deviance	76351 on 57033 df	76272 on 57035 df	76211 on 57032 df
df is degrees of freedom		$^{***}p < 0.0001$; $^{**}p < 0.001$; $^{*}p < 0.006$	

Table 4: Statistical models.

sociation between the legality of abortion and the viewpoint of abortion-related Facebook posts in US states. As abortion legality is considered a categorical variable, the reference group is a class of *Most Protective* abortion policies. The discoveries exhibit that all three categories of restrictive abortion regulations are statistically significant ($p < 0.0001$) revealing that states with restricted abortion policies are more likely to contain abortion opposing posts compared to states with *most protective* abortion policies. In other words, restrictive abortion state laws are correlated with a higher likelihood of disseminating pro-life posts in these states compared to most protective states, confirming H8.

Gender Analysis. To examine the interplay between users' stances about abortion, gender, and other independent and control variables, we re-ran all the models on a sample of posts obtained from Facebook posts, in which the perceived gender was manually labeled. Standard errors were clustered by state and user name, as posts shared by the same user might not be independent. The results obtained from the models suggest that accounts perceived as male are more likely to share posts against abortion compared to accounts perceived as female ($p < 0.0001$). However, we did not find associations between stance and other independent variables, most likely due to the dataset size.

Discussion

Understanding the relationships between the selected variables is a complex issue as there are multidirectional correlations, and variables are somewhat connected. However, this study shows that social media data can be utilized to provide a better understanding of the state population attitudes and the factors associated with them. This study has some limitations. Firstly, the posts gathered to study the public stance regarding abortion are only posted in English, and none of them originated from regular or private Facebook users. Secondly, the fine-tuned stance detection model still needs some improvement to achieve current state-of-the-art performance. However, this is the first study implementing stance detection on abortion using Facebook data. The future work includes examining the opinions regarding abortion on other social media platforms as well as studying the differences in stances before and after the Dobbs v. Jackson ruling. Finally, analysis in different languages might provide a cultural impact on the stances toward abortion in the US.

Conclusion

In conclusion, this study gathered a collection of Facebook posts linked to abortion after the leak of the Supreme Court's decision to overturn Roe v. Wade (Dobbs v. Jackson ruling). Afterward, a ground truth dataset was created to fine-tune the stance detection model that perform sufficiently on the collected dataset. Then, a multivariate regression analysis highlighted the significant relationships found among Facebook posts' stances toward abortion and other contributing factors at the state level in the US. The attributes that were found to be associated with public attitudes were infant mortality rate, number of abortions, abortion legality, and political leaning. Despite the limitations of this study, the results indicate that there is a significant association between state-level health and social compositions and stances expressed toward abortion on Facebook.

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Ethics Checklist

1. For most authors...
   (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes
   (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes
   (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes, in the Hypothesis Formulation.
   (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? NA
   (e) Did you describe the limitations of your work? Yes, in the Discussion section.
   (f) Did you discuss any potential negative societal impacts of your work? NA
   (g) Did you discuss any potential misuse of your work? NA
   (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? Yes. In the Introduction, we state that we only share unique Facebook Page and Group identifiers, which researchers need to pass to the CrowdTangle API to reproduce our dataset.
   (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes
2. Additionally, if your study involves hypotheses testing...
   (a) Did you clearly state the assumptions underlying all theoretical results? Yes, in the Analysis and Results section.
   (b) Have you provided justifications for all theoretical results? Yes, in the Analysis and Results section.
   (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? Yes in the Hypothesis Formulation section.
   (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? Yes, explanations can be found in the Analysis and Results section.
   (e) Did you address potential biases or limitations in your theoretical framework? Yes, in Hypothesis Formulation.
   (f) Have you related your theoretical results to the existing literature in social science? Yes, in Hypothesis Formulation.
   (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? Yes, in the Discussion section.
3. Additionally, if you are including theoretical proofs...
   (a) Did you state the full set of assumptions of all theoretical results? NA
   (b) Did you include complete proofs of all theoretical results? NA
4. Additionally, if you ran machine learning experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? We provided a URL to the Facebook Group and Page ids needed to replicate the dataset in the Introduction.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? Yes, in the Stance Detection section.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? Yes, in the Stance Detection section, we report Macro F1 and accuracy scores in Table 1.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? Yes, in the Stance Detection section.
   (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? Yes, in the Stance Detection section.
   (f) Do you discuss what is "the cost" of misclassification and fault (in)tolerance? Yes, in the Stance Detection Section.
5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? Yes, all the data sources are cited in the paper.
   (b) Did you mention the license of the assets? No, as we are using publicly available datasets.
   (c) Did you include any new assets in the supplemental material or as a URL? Yes, in the Introduction.
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? No, as we are using a publicly available dataset from Facebook.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? Yes, we mentioned that certain characteristics of the users can be obtained, such as perceived gender.
   (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR (see FORCE11 (2020))? In the Introduction, we share the URL to the Zenodo dataset repository, sticking to the FAIR guidelines.
   (g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset (see Gebru et al. (2021))? The Zenodo repository includes a detailed datasheet file where we addressed required questions.
6. Additionally, if you used crowdsourcing or conducted research with human subjects...

(a) Did you include the full text of instructions given to participants and screenshots? NA
(b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? NA
(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? NA
(d) Did you discuss how data is stored, shared, and deidentified? NA