Understanding Narratives of Trauma on Social Media

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ABSTRACT

Background: Victims of domestic and sexual violence often share their narratives on social media. Doing so helps them access validation, solidarity, and support from external sources, which has been shown to enhance resilience and facilitate healing. **Problem Statement:** We address two aspects of such *narratives of trauma*: (1) identifying causal relationships between narrative elements and (2) analyzing the effect of such elements on social support received. **Method:** We retrieved 5561 such narratives from Reddit, a popular online platform. We applied Large Language Models to extract features from these narratives and analyzed them computationally. **Findings:** Our analysis reveals that prolonged abuse increases self-blame and reduces the intent to seek legal advice; the presence of support increases the likelihood of a victim adopting coping strategies; night-time abuse and intoxication are strongly associated with higher rates of violence; victims experiencing nightmares are more likely to provide detailed descriptions of their abusers; suffering economic and familial abuse increases the support received online. Our research thus corroborates leading psychological theories of narrative, social support, and resilience in online stories and contributes to understanding trauma narratives. In this way, our research can facilitate enhanced social support for victims.

CCS CONCEPTS

• **Human-centered computing**; • **Social and professional topics → Gender**; • **Applied computing**;

KEYWORDS

Reddit stories, Sexual violence, Domestic violence

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Warning: This paper contains descriptions and discussions of intimate partner violence, domestic violence, and sexual violence, which may be triggering to some readers.

1 INTRODUCTION

We investigate the narratives that victims of trauma share online, aiming to deepen our understanding of such narratives and thereby facilitate providing practical help to victims. Such narratives are known to be a powerful means for victims to process their experiences while seeking support and validation [3, 24], but their computational study is lacking. We propose a computational method that incorporates insights from leading social science theories.

A *victim* is someone who has experienced harm or abuse inflicted by another person [28]. Victimization due to domestic violence is characterized by patterns of abusive behavior that occur within homes, typically in intimate relationships. Victimization due to sexual exploitation involves nonconsensual sexual acts or coercion and often occurs in tandem with other forms of abuse.

The harms of such violence are well-documented [8, 10, 31, 32] and include mental (e.g., depression, PTSD, and anxiety), physical (e.g., chronic pain and reproductive health complications), and socioeconomic (e.g., job loss, financial instability, and the need to relocate for safety). Together, feelings of shame, guilt, and mistrust disrupt victims' identity (how they see themselves and are recognized by others, shaped by personal experiences, social roles, and culture [7]) and agency ("the socioculturally mediated capacity to act" Ahearn [2]). The social repercussions include how cycles of abuse perpetuate across generations in families and communities.

Despite growing awareness, the stigma of domestic violence and sexual victimization makes victims fear judgment, shame, and retaliation, preventing them from sharing their experiences or leaving abusive situations. The silencing is compounded by emotional ties and fear of consequences—such as losing custody of one's children or financial stability. Such fears and isolation hinder victims' ability to build resilience. Online sharing provides a way out for victims because it facilitates confidential sharing (e.g., using a phone from a bathroom) when face-to-face meetings with supporters may be difficult. Below, we show excerpts of two trauma narratives.

Excerpt 1 is from a post by a minor who was sexually abused by an authority figure. The victim decided to press charges years later and is seeking legal advice.

Excerpt 1 (Reporting and legal advice). *When I was a teenager, my voice teacher who lived in my neighborhood gave me lessons. To save money, I made a deal to do chores for him in exchange for lessons; I called it "Chores for Chords". Long story short, he ended up molesting me a few times, and 14+ years later I've finally gotten a court date on September 1st after charging him with this three years ago. (No, I'm not answering questions like "why did it take you so long"... if you've been through this sort of thing, you'd understand). So he recently plead not guilty, which is why a court date was set. I've been told that his lawyer will attempt to settle with me outside of court for a sum of money before the trial. I've not been able to keep a job for more than two years at a time due to stress (attributed to PTSD for whatever reason). The man is 80 years old, and I've been told by friends of mine that when we go to trial the defense will rip me apart as much as possible. So should they ask to settle, should I take the money?*

Excerpt 2 is from a post by a victim who was sexually abused by an intimate partner. The victim is seeking legal classification of the incident and asking if they are at fault.

Excerpt 2 (Self-blame and legal classification). *A few months ago I hooked up with my ex. A while into things I asked if we could stop and he started going faster. I don't know why he did that or if he even heard me. After I asked and he didn't stop I went into this state of just laying there waiting for it to be over and just watching myself from a distance. Anyway he finished and I was fine. A few weeks after that happened I told a close friend what had happened and she immediately got worried and told me he raped me. Logically I thought it made sense but in context I was very skeptical. I started to think about it more, voluntarily and not voluntarily, and I got pretty uneasy. Eventually this went away and I forgot about it for the most part until a few days ago. I had a really bad episode of flashbacks and dissociation. My initial question is, was this rape? We hooked up again a few days after the initial incident and I was fine still. Does that change the validity of my experience? I feel very bad for even considering the possibility of this being rape because 1) I don't think he even meant anything bad 2) afterwards I was fine for a few weeks and 3) I re-exposed myself to him in an intimate way afterwards. I just need answers right now.*

Trauma narratives have garnered much research attention. Amir et al. [3] find that producing a better-developed narrative shortly after an assault is linked to reduced PTSD severity. Crespo and Fernández-Lansac [12] emphasize the need for refined linguistic measurements and models in understanding trauma memory and adaptation. Meichenbaum [24] studies self-narratives in trauma recovery, noting that inner conversations influence whether victims develop PTSD or resilience. Beeble et al. [5] identify factors that influence willingness to support intimate partner violence survivors, including gender, age, and prior victimization.

However, little computational work focuses on understanding how these narratives affect the support provided to victims on online platforms. We posit that a computational model can help uncover the interplay between narrative attributes (e.g., the setting, characterization, plot) that contain attributes of abuse (e.g., type, pattern, and impact). Accordingly, we propose the following research questions to incorporate insights from studies of narrative and trauma into a computational model for trauma narratives on online platforms.

- **RQ 1:** How do features of victim narratives capturing (1) relationship with the abuser, (2) setting, characterization, plot, and impact of the abuse, and (3) function of the narrative, relate to each other?
- **RQ 2:** What features of victim narratives are most strongly associated with improved social support received in online support communities?

We address these questions through an approach that combines Natural Language Processing (NLP) with causal analysis. Through this approach, we contribute to the broader goal of supporting victims by identifying the impacts of victimization.

Findings in Brief. We investigate the causal relationships between abuse features, coping strategies, and victim responses. We find that prolonged abuse increases victim self-blame (e.g., believing they caused the abuse), whereas singular incidents of violence (i.e., abuse was inflicted once) reduce it. Domestic spaces, intimate partners, and recurring incidents of violence (i.e., abuse was inflicted more than once) are strongly linked to various types of abuse, with nighttime abuse showing a notable pattern. Victims with strong support systems are more likely to confront abusers or report their abuse to authorities, though the perpetrator being a family member tends to hinder these actions, possibly due to stigma or family loyalty.

Victims of authority figures and those who report abuse are more likely to seek legal advice (e.g., whether to pursue formal charges). Sexual abuse is strongly associated with seeking legal classification (e.g., whether the incident described constitutes sexual assault). Recurring abuse often normalizes victimization, reducing the intent to seek legal advice and increasing victim self-blaming. The presence of supporters helps victims sever ties (e.g., divorcing an abusive partner) and cope, whereas antagonists (e.g., unsympathetic people) are linked to trauma symptoms like nightmares. Overall, our findings highlight the importance of support systems along with the effects of abuse patterns and legal systems on victims' coping and recovery processes.

Most features extracted from a narrative, such as abuse type and relationship with the perpetrator, do not significantly affect the online social support received, as measured by comment count. However, narratives detailing economic abuse or abuse by family members significantly increase supportive comments.

Plan of the Paper. The rest of the paper is organized as follows. Section 2 discusses the theoretical framework that we adopt for our study. Section 3 summarizes our computational methodology, encompassing data collection, thematic analysis of our data, and feature extraction. Section 4 discusses our results and connects them with the literature on narratives on trauma. Section 5 concludes the paper with its limitations and broader implications. Section 6 points to supplementary material to aid in reproducing our results.

2 BACKGROUND

Narrative theory [18] highlights storytelling as essential for processing trauma and reclaiming agency. Narrative therapy [22] demonstrates how constructing coherent narratives helps abuse victims make sense of events, express emotions, and rebuild self-worth.

Social Support Theory [19, 33] emphasizes the importance of emotional, informational, and practical support from friends, family, therapists, and online communities in mitigating the effects of stress and promoting psychological well-being [11]. Interestingly, the belief that emotional support is available has a stronger influence on mental health outcomes than the actual support [15, 35].

Resilience Theory emphasizes the ability of people to recover from adversity. It suggests that resilience is not merely the ability to bounce back but involves growth through adversity, shaped by both internal and external resources, as elaborated in Masten [23].

Computer-Mediated Communication (CMC) [34] theory explains how digital spaces enable people to communicate without the constraints of physical presence, often fostering more openness, vulnerability, and emotional expression. CMC facilitates helpers across geographical and social boundaries to offer emotional support and practical advice and thus helps victims reduce isolation, build resilience, enhance psychological well-being, and work toward recovery [29].

Table 1 summarizes how this study pulls these theories together. Narrative Theory emphasizes the importance of articulating the trauma. Social Support Theory highlights the benefits of external support. Resilience Theory refers to the process of growing through adversity. CMC Theory helps us understand online interactions.

Table 1: Summary of psychological theories.

Theory	Motivation for inclusion in this study
Narrative Theory	Storytelling is a tool for processing trauma, reclaiming agency, and reshaping identity *(RQ1)*
Social Support Theory	Emotional, informational, and practical support is crucial in reducing stress and enhancing well-being *(RQ2)*
Resilience Theory	Narratives of coping and support show growth through adversity, reflecting strength *(RQ1, RQ2)*
CMC Theory	Digital interactions influence communication, relationships, and social behavior *(RQ1, RQ2)*

RQ 1 links to *Narrative Theory* by examining storytelling for processing trauma and to *Resilience Theory* by exploring coping mechanisms. RQ 2 links to *Social Support Theory* by identifying features driving support and *Resilience Theory* by showing how coping actions may foster resilience. Both RQ1 and RQ2 link to *CMC Theory* by examining how digital interactions shape narrative expression and social support in online communities.

Approach in Brief. Figure 1 provides an overview of our approach. We focus on four moderated subreddits, namely, r/domesticviolence, r/metoo, r/SexualAssault, and r/SexualHarassment where a victim may share their trauma story and receive support, practical advice, or validation of their emotions and experiences.

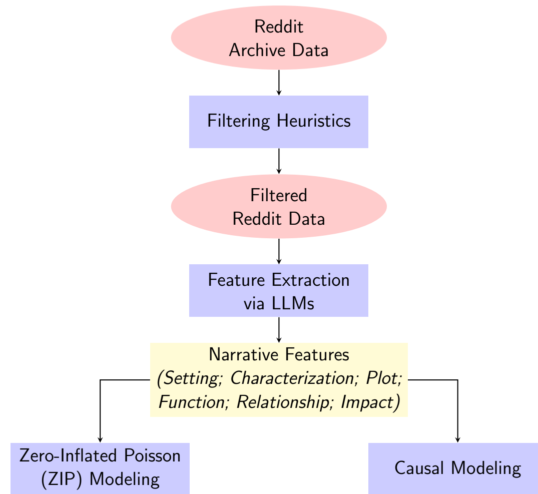


Figure 1: Overview of our approach. We begin with raw Reddit data, which we filter to retain only the posts relevant to our study. We apply large language models to extract the key narrative features from these posts. These features are used as inputs for statistical and causal models to analyze narrative patterns and their underlying dynamics.

Reddit's structure makes it well-suited to such sensitive discussions. The above subreddits are moderated by community volunteers who ensure compliance with site rules, such as promoting respectful interactions and prohibiting doxing—revealing users' identities based on their posts. Moreover, moderators may provide access to local help hotlines in cases where life-threatening situations are described.

Reddit supports long, detailed posts, which often adhere to standard English. This makes Reddit posts amenable to NLP techniques. We adopt Llama 3.1 8B Instruct [14] to extract the features detailed below. Using these features, we implement a causal model of our hypothesized directionalities and a zero-inflated Poisson (ZIP) model to identify the features that most influence the social support received.

3 APPROACH

We first collect and validate Reddit posts from relevant subreddits. Then, we conduct a thematic analysis to extract key narrative elements. Next, we use Large Language Models (LLMs) to systematically label these features and apply causal modeling to uncover relationships between them. Finally, we employ a ZIP model to examine how these narrative elements influence engagement, measured as the number of comments received by a post.

3.1 Data Collection

We obtained archived Reddit posts from r/domesticviolence, a relevant *subreddit* or forum. We retained posts written by victims of sexual violence or domestic violence, whose titles included first-person pronouns (*me*, *mine*, *myself*, *I*) and which included selected key words, yielding 710 relevant posts. We combined this data with a previous dataset [16] containing data from the subreddits r/sexualharrassment, r/MeToo, and r/SexualAssault, yielding 5561 posts. We validated this data with a random sample of 50 posts from each subreddit, achieving a weighted accuracy of 91.89%.

3.2 Thematic Analysis of Narrative Elements

We employed thematic analysis [27] to identify and categorize narrative features in Reddit posts related to experiences of abuse. Specifically, we adopted the reflective thematic analysis [6], a flexible and interpretative method where themes are developed through an iterative process, emphasizing the researcher's participation in making meaning rather than rigidly applying a coding framework. This process was systematic, iterative, and grounded in qualitative analysis principles to ensure comprehensive coverage of the relevant features.

Initial Familiarization We reviewed over 100 randomly sampled Reddit posts to identify recurring themes and patterns, which helped us develop broad categories to capture key aspects of the narratives, as detailed below.

- **Precursor:** Information describing the situation before the abusive relationship, such as the nature of the relationship (e.g., intimate, familial, or professional).
- **During Abuse:** Features describing the abusive event. These features include the setting, characterization, and plot [26]. Setting (S) refers to the *where* and *when* of a narrative. Characterization introduces the *who* in the story. Plot captures the *what* of the story. For our purpose, *Setting* describes the location, environment, and pattern of abuse, *Characterization* describes the victim's self-blame, the detail of the abuser's mention, and supporters or antagonists involved, and *Plot* describes the type of abuse and the victim's coping actions.
- **Aftermath of Abuse:** The effect of violence on the victim reflects the depth of trauma and underscores the victim's immediate and long-term needs.
- **Present Day:** The author's stated intention in sharing their story online, e.g., what they hope to achieve by it.

Generating Initial Codes Using these broad themes, we reread the posts to capture meaningful instances. We assigned codes according to phrases or sentences aligned with the identified themes. Table 3 lists some highlighted sentences.

Refining Themes and Defining Categories We refined the themes to accurately represent all aspects of the narratives, resolving overlaps and clarifying ambiguous codes. To ensure consistency, we grounded the final features in the existing literature on trauma, abuse, and narrative analysis. For instance, we replaced "Abuser's portrayal" with "Abuser discussed in detail" since some descriptions depicted abusers as manipulative, whereas some didn't mention the abuser at all. We removed "Eating disorders" and "Sleeping disorders" due to their infrequent appearance. Similarly, we revised the "Mental health" category. Initially, this category was split into "Depression," "Anxiety," and "PTSD." However, since diagnosing these disorders requires professional evaluation, we instead introduced "Nightmares" to capture intrusive memories and flashbacks after abuse.

Expert Validation of Features A developmental health researcher with expertise in trauma and adversity exposure reviewed the categories to ensure alignment with psychological constructs and accurate representation of abuse victims' experiences.

Feature Extraction Using LLMs We automated feature extraction from the posts using an LLM, assigning the refined categories as labels, and classifying each post according to whether each feature is present or absent.

Ensuring Robustness To validate the feature extraction, we cross-referenced LLM outputs with manual annotations for a subset of posts to determine if the automated outputs align with the thematic framework.

Table 2 describes the features we define within these groupings. Table 3 provides examples of these features as seen in our dataset.

3.3 Feature Extraction via LLM Prompting

An LLM is a deep learning-based AI trained on vast corpora of textual data, enabling it to generate and comprehend natural language. By leveraging transformer architectures, LLMs capture complex linguistic patterns, facilitating tasks such as text generation, machine translation, and question answering. We used an LLM to extract the features from Reddit posts, specifically Llama 3.1 8B Instruct, fine-tuned for instruct prompting [14]. Using prompt engineering, we extracted narrative elements including the categories of relationship, setting characterization, plot, impact, and function. We use a combination of zero-shot prompt engineering, few-shot prompt engineering, and chain-of-thought prompt engineering for the various features. We employ the beam search algorithm as our text-generation decoding strategy [17] since our features are binary. Each output of the LLM was evaluated on a manually annotated dataset of 50 posts, obtaining an average F1-Score of 0.71. The output of the LLM was restricted to "Yes" or "No." For the exceptions where the LLM output something other than these values, it was replaced with "No."

3.4 Causal Model

We employed causal modeling to better understand how the features relate to each other.

3.4.1 Causal Inference Framework. A directed acyclic graph (DAG) represents assumptions on causal relationships. We identify variables of interest—such as *Type of Abuse*, *Relationship*, *Self-Blame*, and *Intention*. We define a causal graph whose nodes are the extracted features and which has a directed edge from one feature to another whenever there is a (possible) direct causal effect of the source feature on the target feature. We lack the space to include a graph here but see Section 6.

For example, an edge from *Intimate Partner* to *Type of Abuse* indicates that an intimate partner perpetrator may directly influence the type of abuse experienced by the victim. The DAG helps identify confounders, i.e., variables that influence both the cause and the effect, and which could thus bias the estimated causal effect. We used the DAG to obtain adjustment sets for causal models, ensuring that potential confounders were accounted for during the estimation of causal effects. Under standard causal assumptions, we make use of the Outcome Regression (OR) estimator [20] to assess

Table 2: List of included features with examples of their values and our motivations for including them. Here, R, S, C, P, F, and I, respectively, refer to Relationship, Setting, Characterization, Plot, Function, and Impact.

Feature	Possible values (examples)	Motivation for inclusion in this study
R: Relationship	Intimate partner, authority figure, stranger	Shapes victim's connection to the abuser and nature of abuse
S: Location	Domestic, professional, social, public, cyber	Influences safety, visibility, control, scope to intervene
S: Environment	Night-time, intoxication	Influences abuse type and severity
S: Pattern	Singular, recurring	Depicts the severity and complexity of trauma
C: Self-blaming	Not ending the abuse, enabling the abuser	Captures psychological impact and barriers to recovery
C: Abuser	Abuser described in detail	Influences reader's perception of abuser
C: Characters	Supporters, antagonists mentioned	Highlights supporters' aid and antagonists' harm
P: Type of Abuse	Physical, verbal, sexual, economic	Highlights nature and severity of trauma experienced
P: Coping	Confrontation, reporting, severing ties	Indicates victim's resilience and agency
F: Intent	Seeking legal classification, advice or support	Highlights why victims share their stories
I: Mental	Nightmares	Curtails recovery via flashbacks and nightmares
I: Physical	Injury	Reflects the extent of physical harm caused by the abuse
I: Economic	Financial instability, legal barriers	Highlights socioeconomic burdens faced by the victim.
I: Behavioral	Self-harming	Indicates self-destructive behaviors and suicidal thoughts

the difference in probability of a particular event occurring or an aspect being present, depending on the presence of another factor. We fit the potential outcomes using logistic regression and estimate the variances of predicted values using the Delta method [13].

3.5 Zero-Inflated Poisson Model

We employ a ZIP model to predict the number of comments, which serves as a measure of social support received. Specifically, we define *supportive comments* as those made by users other than the victim. A manual annotation of 50 randomly sampled comments, revealed a high relevance rate of 97%. The ZIP model is suitable for this task because our dataset contains a large number of posts with zero comments. In such cases, a standard Poisson model would struggle to handle the over-representation of zeros, which is common in count data where a substantial portion of observations result in no events (comments, in this case).

causing variance to be greater than the mean. In such cases, a standard Poisson model, which requires the variance and mean to be equal, The ZIP model combines two components:

A binomial model to model the probability that a post will receive zero comments. This part of the model adjusts for the overdispersion caused by the excess zeros in the dataset by predicting whether a post will have no comments at all. We assume that the existence of posts with zero comments is an inherent characteristic of the respective subreddit and independent of the post.

A Poisson count model to predict the number of comments for posts—appropriate here since the events (comments) are independent.

We iteratively removed statistically insignificant features from the Poisson count model to retain only the features that were significant in predicting the number of relevant comments. We begin with all the features and iteratively remove the most insignificant feature until only features with p-values less than 0.05 remain. By conducting this ablation study, we ensured that the final model was both accurate and interpretable, with minimal complexity.

4 RESULTS & DISCUSSION

We now present the results of our proposed approach, addressing our research questions and discussing the key findings.

4.1 RQ1: Causal Model

We answer RQ1 by finding causal effects between hypothesized cause and effect pairs of features. The causal model described in Section 3.4 tells us if our hypothesized models are significant, i.e., there exists a directionality between the chosen features, quantified by the p-values. Since we test each of these hypothesis individually, we consider a p-value less than 0.05 as significant. We tested a total of 261 cause-and-effect pairs, 259 of which showed significance. In the remainder of this section, we only discuss the significant cause and effect pairs ($p < 0.05$). Note that not all causal relationships are shown in the figures; we focus on only the most intriguing findings, excluding those with a causal estimate below 0.01 due to space constraints. The full paper (see Section 6) includes a complete analysis of our work.

Figure 2 shows the features that have a significant effect on the types of abuse. Shedding light on the power structures in different types of relationships, we observe that intimate partners are more likely to physically and sexually assault victims, whereas authority figures and colleagues are more likely to sexually harass or economically abuse victims. Professional spaces have a negative influence on all types of abuse, potentially suggesting that workplaces have more formal reporting mechanisms that deter abuse. Stranger perpetrators show a similar trend. Domestic, public, and social spaces in general increase all abuse types, with public spaces strongly influencing physical abuse and social spaces strongly influencing sexual harassment and assault. Economic and technological abuse follow similar trends but with weaker influences.

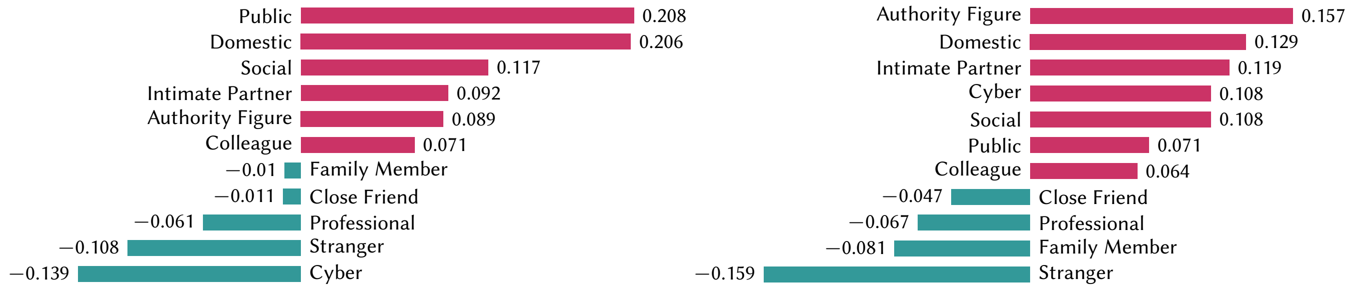
Figure 3 shows the features that have a significant effect on the victim's self-blaming. Victims of all types of abuse tend to self-blame for enabling the abuser. However, only four of these types of abuse are associated with self-blame for not ending the abuse sooner; economic abuse and sexual assault show no significant influence

Table 3: Examples of the main features as seen in our dataset.

Category	Feature	Narrative text from which identified
Relationship	*Intimate partner*	We were married at 20 after a black eye, a torn off toenail, many hairs pulled, my neck choked …
	Family member	When i was 9 my grandfather molested me.
	Close friend	… we met at a work party some time back and we became fast friends … he started groping me
	Colleague	… a coworker had hit on me multiple times and i rejected his advances …
	Authority figure	Let's call my boss " Bill" … from october 2013 to march 2014 bill raped me 5 times
	Stranger	This person started talking randomly about how they were horny on a public voice chat
Location	*Domestic*	I let him stay in my room for 3 weeks … He would place his hands close right under my breasts
	Social	… a Halloween party for our friend group … I wake up to him with his head in between my legs
	Professional	i am a manager at a grocery store … she started humping the side of my leg and grabbed my dick
	Public	He just pushed his groin into me in a public space it was disgusting
	Cyber	and this guy used to make me send him explicit images and videos when I was clearly uncomfortable
Environment	*Night-time*	… waking up without pants on, at 3 am, with him in my bedroom, on my bed
	Intoxicated	He pulled me onto him, touched me and I kept telling him to stop. I was incredibly drunk …
Pattern	*Singular*	So back in 2019 day after Thanksgiving I was assaulted sexually.
	Recurrent	… on several occasions he would have sex with me while I explicitly told him to stop …
Self-blame	*Not ending the abuse*	I definitely should've cut him off much sooner than I did
	Enabling the abuser	I still feel this is my fault for not keeping my boundaries and for not refusing till the end
Abuser	*Discussed in detail*	He was controlling and manipulative and I felt compelled to message him regularly every day
Characters	*Supporters*	My dad found me, and he held me. Told me it wasn't my fault.
	Antagonists	Even my parents told me to shut up and stop asking for sympathy because it was my fault.
Type of Abuse	*Physical*	There isn't a place you could hit, kick or spit on me that he didn't.
	Verbal	He makes us believe that we are worthless and without him we'd be living on the street.
	Economical	18 months later I'm an emotional wreck, mostly unemployed and drowning my sorrows with girls
	Technological	they started to spam me and send me links to adult sites and saying some awful things
	Sexual harassment	While we were having a break, he began to watch porn next to me and masturbate.
	Sexual assault	She groped my breasts, my ass and would shove her hand up my skirt …
Coping	*Confrontation*	Once, I tried to speak to her about it and she laughed in my face
	Reporting	We decided to call the police, as she was very distraught by it, and I was furious.
	Severing ties	I left her and everyone in our friend-circle behind and had a 3 month nervous breakdown.
Intent	*Legal classification*	I didn't touch him once, I constantly told him to stop … Is this sexual assault?
	Legal advice	… but according to agents, these charges aren't enough to deport … looking for advice
	Seeking support	I'd really appreciate your comments on if there's something I could do to help the situation
Mental	*Nightmares*	I've had nightmares of being sexually trafficked, assaulted, and my father raping me.
Physical	*Injury*	My boyfriend strong armed me into the corner and then to the floor hitting me and tossing me …
Economic	*Financial instability*	Once we're divorced, she'll have no financial control over my life and I can rebuild.
	Legal barriers	… even though we have messages of him confessing to it. Yet he's still not arrested.
Behavioral	*Self-harming*	I don't want to die for pity; I wanna die because I don't think I deserve to be alive.

on this form of self-blame. Aligning with social support theory, the presence of supporters negatively influences victim self-blaming and that of antagonists has a positive effect. Kennedy and Prock [21]'s work shows that supporters help break the cycle of stigma by offering validation and reducing self-blame, whereas antagonists reinforce shame and internalized stigma through judgment and disbelief, deterring disclosure and worsening mental health outcomes.

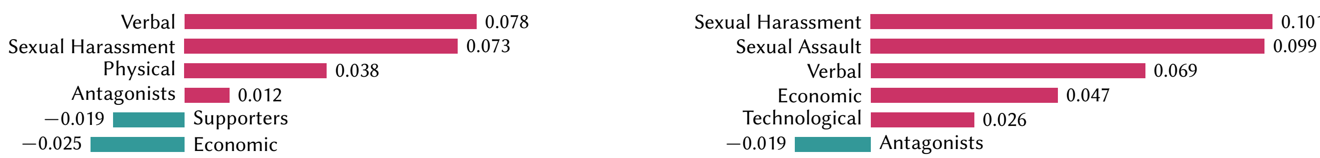
Figure 4 shows the features that have a significant effect on coping strategies employed by the victim. The consistent positive effect of the presence of supporters across all coping strategies highlights the value of support systems to abuse victims' resilience. Though all abuse types lead to victims coping, certain forms of abuse are more strongly associated with coping strategies. Verbal abuse leads to confronting the abuser, whereas sexual assault and harassment lead to severing ties with the abuser. It is interesting to note that all abuse types have a much weaker influence on reporting



(a) Physical abuse **(b) Verbal abuse**

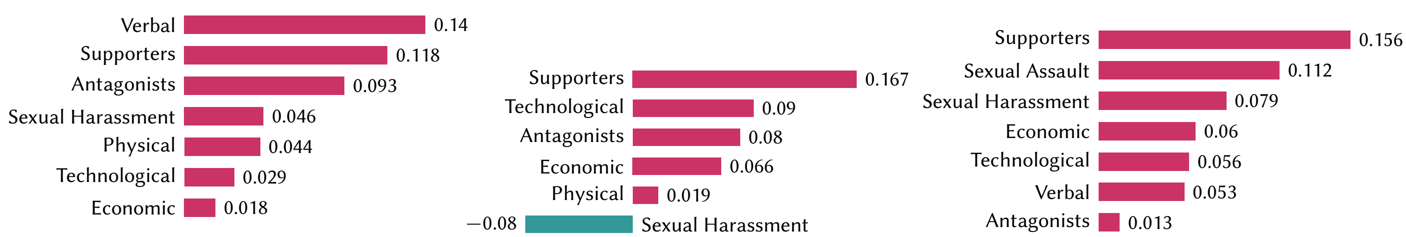
(c) Sexual assault **(d) Sexual harassment**

Figure 2: Effects of various features on types of abuse. Here, the x-axis is the causal estimate.



(a) Not ending abuse **(b) Enabling abuser**

Figure 3: Effects of various features on types of victim self-blaming. Here, the x-axis is the causal estimate.



(a) Confronting abuser **(b) Reporting to higher authorities** **(c) Severing ties with the abuser**

Figure 4: Effects of various features on types of coping strategies. Here, the x-axis is the causal estimate.

to higher authorities than other coping strategies. In fact, sexual harassment has a negative association with reporting to higher authorities along with the victim's intent to seek legal advice (as is elaborated below), possibly reflecting a combination of societal minimization of harassment relative to other forms of abuse and the lack of conclusive evidence for harassment.

We find that the presence of authority figures and colleagues as perpetrators is important; they positively influence seeking legal advice but negatively influence seeking legal classification. Similarly, victims of economic and technological abuse have a higher tendency to seek legal advice but not support, indicating that victims of these forms of abuse prioritize tangible solutions over emotional validation. Moreover, victims suffering from legal barriers and financial instability seek legal advice, as Excerpt 1 in Section 1 shows.

In contrast, as Excerpt 2 in Section 1 shows, intimate partners and close friends as perpetrators positively influence seeking legal classification. Victims of sexual assault and harassment also show a similar pattern of seeking legal classification and support but are unlikely to seek legal advice, affecting it negatively. This may reflect victims' uncertainty about consent in close relationships and the need for validation, clarity, and emotional support. Similarly, victims suffering from physical injuries, self-harm, and nightmares seek support, with a negative influence on seeking legal advice or classification, indicating that psychological distress may prioritize emotional coping over formal legal action.

Family member perpetrators negatively influence seeking legal counsel or support, possibly due to financial dependence, the emotional complexity of exposing abuse within the family, or the social stigma. Barnwell [4] examines how families conceal certain problems, such as abuse, to manage avoid the stigma. Stranger perpetrators also negatively influence seeking legal counsel or support.

Severing ties is the only coping strategy positively influencing the intent to seek legal classification. Coping by confronting the abuser or reporting the abuse positively influences seeking legal advice but reduces the need for support and legal classification, suggesting that taking formal action reduces the need for community reassurance, thus shifting the focus away from personal narratives to legal processes.

Figure 5 shows the features that are affected by the pattern of abuse. The general trend positively associates recurring incidents of violence with all types of abuse, victim self-blaming, nightmares, physical injuries, and the adoption of coping strategies. In contrast, singular incidents of violence show negative associations with these features. This underscores how chronic abuse escalates over time, both in severity and its psychological toll on victims. This pattern aligns with findings from prior research. Miller and Porter [25] state that as the duration of abuse increases, self-blame in battered women shifts from responsibility for the abuse itself to responsibility for its continuation. Cascardi and O'Leary [9] report that victims often self-blame, which can manifest as behavioral self-blame (e.g., believing their actions provoked the violence) or characterological self-blame (e.g., believing they have inherent flaws that make them deserving of abuse), with the distinction between the two varieties often blurring over time.

However, seeking legal classification is the only feature that is positively influenced by singular incidents and negatively influenced by recurring incidents. This may indicate that victims of ongoing violence may become more aware of their abuse over time.

Night-time abuse and victim's intoxication show only positive associations with many factors, aligning with crime data showing higher rates of intimate partner violence at night when abusers have more control over the victim's environment [30].

Abbey [1] claims that alcohol increases the likelihood of sexual assault by impairing perpetrators' cognitive processing and increasing aggression, making them more likely to commit sexual assault, while also reducing victims' ability to recognize danger, resist, or recall details accurately.

Several factors—including authority figures and intimate partner perpetrators, verbal, physical, sexual, and technological abuse, night-time abuse, and the victim's intoxication—have positive effects on detailed descriptions of the abuser being present in the narrative. These effects possibly indicates an alignment with narrative theory that claims that describing one's traumatic experiences can aid in processing trauma.

4.2 Zero-Inflated Poisson Model

We answer RQ2 by employing our ZIP model to identify the narrative features that significantly predict the number of supportive comments received by trauma narratives in online support communities. Our ablation study, which iteratively removed statistically insignificant features, reveals that the majority of examined features do not significantly affect the level of social support, as measured by comment count. Specifically, features such as the type of abuse (e.g., physical, sexual, or verbal), the victim-perpetrator relationship (e.g., intimate partner, stranger, or colleague), and contextual factors (e.g., time of day, location, or presence of legal barriers) do not significantly influence comment volume. This suggests that these specific aspects of trauma narratives do not strongly drive online community engagement.

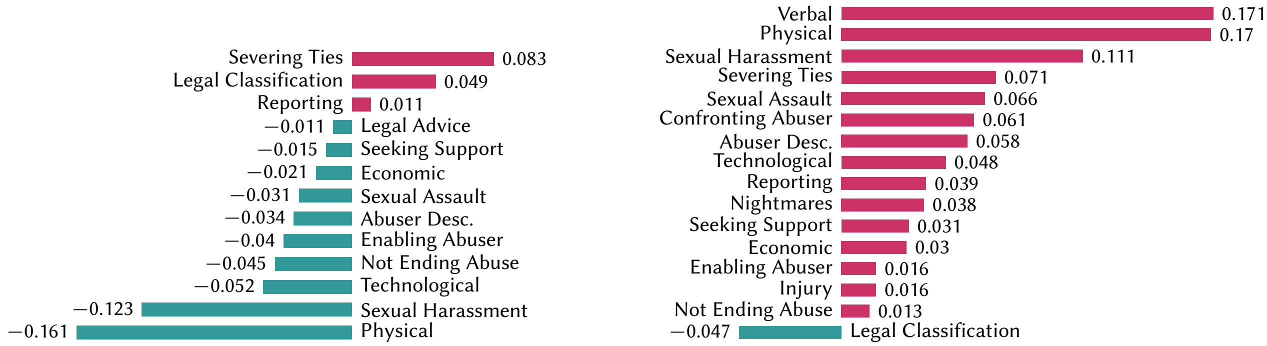
However, we observe two notable exceptions: economic abuse and family member perpetrators. These two features significantly predict an increased number of supportive comments ($p < 0.05$). This indicates that narratives detailing financial exploitation or instability particularly resonate with online supporters. Similarly, narratives involving familial abuse may evoke a stronger sense of empathy or urgency within the community. Interestingly, though familial abuse may prevent victims from seeking legal counsel or support (as depicted by our causal model), it increases the support received.

5 CONCLUSIONS

Our findings highlight the complex interplay between abuse characteristics, victim responses, and contextual factors. Recurring abuse, intimate partner perpetrators, and domestic settings greatly influence victim self-blame, coping strategies, and intent. The presence of supporters is instrumental in empowering victims to sever ties and report abuse, whereas legal intervention appears less viable for prolonged abuse cases. The strong influence of night-time and intoxication on various abuse dynamics reinforces existing criminological insights.

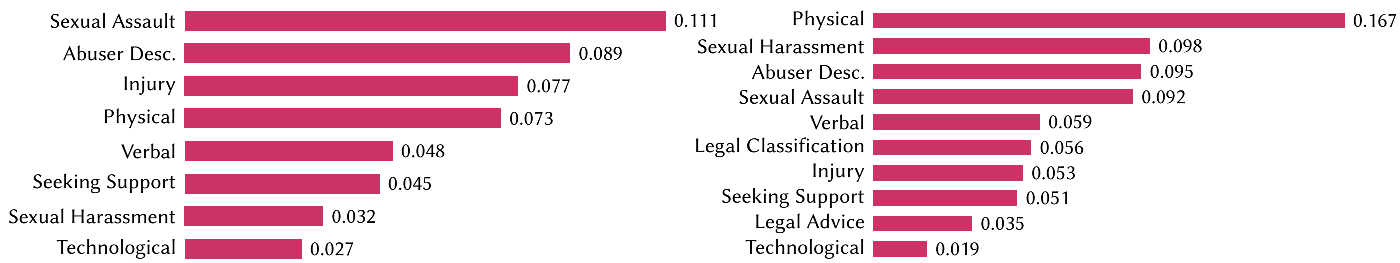
These narrative features align with established theories of trauma recovery, including *narrative theory*, *social support theory*, and *resilience theory*. Adopting these theories helps us understand how the victims' ability to share their stories and receive emotional validation in online spaces contributes to their resilience and recovery. Ultimately, our study underscores the need for targeted interventions that address the specific challenges victims face based on the nature of abuse and their relationship with the perpetrator.

Our ablation study reveals that most features we examined—including the type of abuse, the relationship with the perpetrator, and various contextual factors—do not significantly influence the number of comments on trauma narratives. This indicates that these features are not important in eliciting social support through online



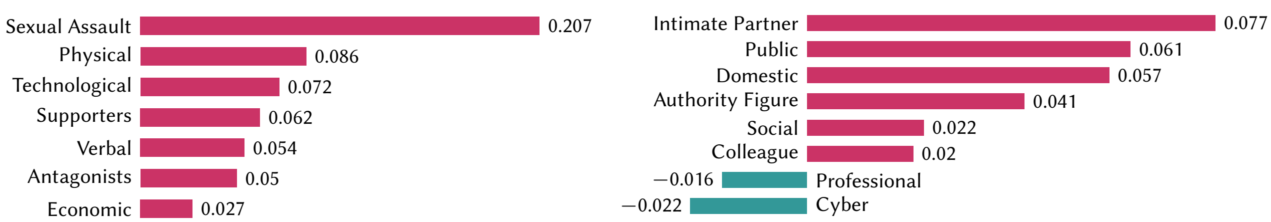
(a) Singular incident **(b) Recurring incidents**

Figure 5: Effects on various features by the pattern of abuse. Here, the x-axis is the causal estimate.



(a) Victim's intoxication **(b) Night-time abuse**

Figure 6: Effects of various features by the environment of abuse. The x-axis represents the causal estimate.



(a) Victim experiencing nightmares **(b) Physical injury**

Figure 7: Effects of various features on impacts experienced by the victim. The x-axis represents the causal estimate.

comments. However, only economic abuse and family member perpetrators emerged as significant predictors, highlighting the importance of these particular aspects in driving engagement and responses from the online community.

5.1 Limitations and Future Work

This study may not generalize broadly, as platform-specific demographics and norms may shape how victims disclose their experiences. Expanding the data to include additional online platforms, especially those prominent outside the US and in languages besides English, could provide a broader understanding of how social support manifests across different cultural milieus. Another limitation is that we quantify social support received by the number of comments received. Future work can investigate how the content of these comments affects victims' sense of validation and emotional recovery. This could involve examining whether the frequency of certain types of comments appearing on posts depends on the features identified in the narrative. In addition, it would help to include longitudinal studies to explore how the evolution of a victim's narrative over time interacts with their engagement in online communities. By examining how trauma narratives change as victims receive more support, we could gain insights into the influence of the collective dynamics of online communities on a victim's recovery.

5.2 Broader Implications: Benefits and Risks

This study highlights key implications for designing online support communities and enhancing trauma recovery through digital platforms. Online spaces provide victims with opportunities for emotional support, experience sharing, and validation. By focusing on narrative-driven elements, platforms can support resilience and recovery, helping victims regain agency. However, online support spaces present risks, such as exposure to further trauma, cyberbullying, or victim-blaming, which can hinder recovery. Ensuring that platforms have safeguards to promote a supportive environment is crucial. The anonymity of online interactions, though facilitating open expression, may lead to toxic behaviors, making effective moderation essential. Additionally, reliance on online support over face-to-face interactions may limit access to more comprehensive psychological care. That is, though online support communities offer valuable resources for victims of violence, balancing the benefits of anonymity with the need for safe, accountable engagement is vital. Further research on platform design is necessary to maximize the benefits while mitigating potential harms.

6 REPRODUCIBILITY

Our dataset contains sensitive stories, so we will share it only with accredited researchers upon request. The code, supporting descriptions about the features and models, and extended results are available at https://github.com/saxenamansi/TraumaNarratives.

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