The Digital Dynamics of Social Movements: The Case of #MeToo

Hubert Au

St Antony's College

University of Oxford



Supervisors: Professor Philip N. Howard and Dr. Chico Camargo

Thesis submitted in partial fulfillment of the requirements for the degree of DPhil in Social Data Science in the Oxford Internet Institute at the University of Oxford

Word Count: 50,000 words

April 19, 2024

Abstract

In October 2017, American actress Alyssa Milano called for other survivors to say 'Me Too' on Twitter. From that tweet sparked the #MeToo movement, spreading to at least 85 countries with variations from #MoiAussi in France, #QuellaVoltaChe in Italy, to # 米兔 in China. #MeToo remains the most enduring instance of feminist activism in recent years, entering the everyday lexicon on sexual violence and continuing to make headlines and shape discussion at the highest levels of public scrutiny. Despite a growing body of scholarly work on digital activism, much remains to be understood about how at a global level digital feminist activism is diffused through social media such as Twitter, its impacts on public understandings of sexual violence, and how collective memory of those movements can be influenced and contested by movement participants. These would lead to a deeper understanding of what makes modern feminist movements successful transnationally. This project poses questions wider in temporal and geographic scope, possible now as the movement has taken root in countries as recently as 2023, combining the theoretical grounding of social movement literature and feminist scholarship with mixed methods. The central research question posed is: What was the effect of #MeToo on international discourse on sexual violence? This is broken down into three studies asking: (a) What effect did social media dialogue between activists have on the transnational diffusion of frames in #MeToo activism on Twitter? (b) What effect, if any, did #MeToo have on media representations of sexual violence, and are these effects lasting? (c) How are digital collective memories of #MeToo formed? This thesis additionally develops new computational social science methodologies to study transnational social movements: the development of new agent-based modeling is used to model social movement diffusion theory, and multilingual natural language processing techniques paired with qualitative coding of rape myths in the media allow for the study of #MeToo in greater depth than existing literature encompasses. Articles I and II reveal that individuals are able to initiate across borders positive change and engagement in the discourse around sexual violence, whereas institutions even in countries with lower media controls and higher women's empowerment are much slower at adopting feminist perspectives if they do so at all. Finally, Article III foregrounds the importance of collective memory in shaping societal change and influencing future feminist movements, examining the digital collective memories of #MeToo formed across a variety of platforms and languages, from Wikipedia, TikTok, YouTube, to curated archives. This thesis argues that the dynamics of contemporary transnational movements are significantly distinct from traditional movements, and for the the importance of collective, individual contestation of memory and meaning making beyond the English-speaking world.

Keywords #MeToo - Computational Social Science - Social Movements - Feminist Activism - Natural Language Processing - Agent-Based Modeling

Acknowledgments

I am grateful for the guidance and support of my supervisors, Phil Howard and Chico Camargo. I am grateful also to the assessors whose feedback has always been valuable over the course of my DPhil: Brooke Foucault Welles, Susan Banducci, Scott Hale, Kathryn Eccles, and Ana Valdivia.

I would like to direct a special thank you to Chico, in whom a unique confluence of technical expertise and critical faculty along with a supportiveness, understanding, straightforwardness, and brightness always enabled me to feel comfortable around yet challenged to be clearer, better, and more incisive in my academic thinking. Thank you for enduring my 'monkey-brain' drafts and research ramblings, for making Exeter and the CCLab welcoming and inviting, and for lifting me up professionally wherever you could.

Thank you to all the research colleagues I have had the pleasure of working with along the way: Nahema, Yung, Lisa-Maria, Aliaksandr, Anna, Mona, and Egerton especially at the Programme on Democracy and Technology and at the International Panel on the Information Environment. Thank you also to Joana for being a great collaborator for one of my chapters.

I have also been lucky to have had the support of brilliant people at the OII. Chrissy, thank your generosity, positivity, and compassion that shines through all the time when you go our of your way to make students' lives better. Thank you for sitting through my first TA session when you didn't have to, and thank you for sharing lunches with me in a ghostly department mid-pandemic. Thank you to Kathryn for running excellent DPhil seminars that consistently made the degree feel more approachable, and for running the much needed virtual welfare check-ins when we couldn't gather in person.

A personal thank you to all the wonderful people with whom I have had the privilege of spending the last few years in Oxford with. Thank you to Srujana for sharing our house on Divinity Road together, suffering through all the noise I made on the piano, and for all the shows I would have never discovered with you; to Yung for being an inspiration with all the labor you have put in on behalf of myself, other DPhil students, and anyone in need whilst hosting hot pots to bring me a little closer to home; to Julia, for all the dreamy afternoons at Henley and for always being up for a game of Chess or Go; to Nayana for all your passion, song recommendations, and for being such an attentive friend; to Patrick for staring at a wall with me; to Nancy for all delicious dinners at Juxon St and for and showing me Cairo; to both Rutendo and Nancy for enduring the soulless basement office with me; to Maggie and Sam for Superbowl nights I always look forward to; to Alexa for tolerating some early drafts of my chapters; to Joanna and Paul for endless creativity, humor, and cocktails; to Siân for always believing in me, always being straightforward, and for being an incredible inspiration; to Amanda for combining the joys of gaming with academia for me; and Paul R. for your generosity, camaraderie, and kindness on and off the Rift; to Moritz and Nahema for your kindness to me during the harsh lockdowns; to Mona for your cheerfulness

and being the best *teta* one could ask for; to Felix for your wit, smiles, and random facts about small German towns; to Rifky for challenging me to be a better tennis player and letting me win a few sets; to Suyash for being a wonderful and personable M5 captain and doubles partner; to Yin, for having introduced me to the OII in the first place; to Ryan, with whom I am so happy I got to share some time in Oxford; to Joe, Ploy, and Leon for having been my tailwind since 2014. Lastly, I owe immensely to Inda, thank you for sharing your love with me, I can't imagine the last few years without you.

This thesis would not have been possible without all of you. From the bottom of my heart, thank you.

Table of Contents

Abstract iii

Acknowledgments v

List of Figures xi

List of Tables xiii

1 Introduction 1
- 1.1 Background and Rationale . . . 1
- 1.2 Research Questions . . . 8
- 1.3 Thesis Structure . . . 8

2 Literature Review 11
- 2.1 Social Movements . . . 12
  - 2.1.1 Collective Action . . . 12
  - 2.1.2 Structurelessness in Feminist Movements . . . 13
  - 2.1.3 Digital Media and Connective Action . . . 14
  - 2.1.4 Feminist Digital Activism . . . 17
  - 2.1.5 Broadening Connective Action Paradigm: Diffusion, Media, and Collective Memory 17
- 2.2 Related Work on #MeToo . . . 19
  - 2.2.1 The Role of Organizations . . . 19
  - 2.2.2 Participation . . . 19
  - 2.2.3 Comparative Scholarship . . . 21
  - 2.2.4 Computational Approaches . . . 22
- 2.3 Conclusion: Transnational Social Movements . . . 24

3 Article I: The Transnational and Multilingual Diffusion of #MeToo 25
- 3.1 Introduction . . . 25
- 3.2 Motivation and Contribution . . . 25
- 3.3 The Diffusion of Social Movements . . . 27
  - 3.3.1 The Mechanisms of Diffusion . . . 27
  - 3.3.2 Diffusion and Feminist Movements . . . 29
- 3.4 Limitations of Twitter as a Diffusive Medium . . . 30
- 3.5 Research Questions and Hypotheses . . . 31
  - 3.5.1 Hypotheses . . . 31
- 3.6 Data . . . 33
  - 3.6.1 Data collection . . . 33
- 3.7 Methods . . . 37
  - 3.7.1 Statistical Models . . . 37
  - 3.7.2 Social Contagion . . . 40

3.7.3 Agent-Based Modeling . . . 42
3.8 Results . . . 47
3.8.1 Statistical Models . . . 47
3.8.2 Agent-based models . . . 47
3.9 Discussion and Conclusion . . . 55
3.10 Future Work . . . 57

4 Article II: The Effect of #MeToo on Rape Myths in the Media: A Global Multilingual Analysis 59
4.1 Introduction . . . 59
4.2 Related Work . . . 61
4.2.1 Social Movements and the Media . . . 61
4.2.2 Feminist Scholarship on Media . . . 64
4.2.3 Feminist Scholarship on Media in the #MeToo Context . . . 66
4.2.4 Computational Approaches to Framing . . . 68
4.3 Research Questions . . . 69
4.4 Hypotheses . . . 69
4.5 Data . . . 70
4.6 Methods . . . 72
4.6.1 Rape Myths . . . 72
4.6.2 Annotation . . . 74
4.6.3 Modeling . . . 75
4.6.4 Political Opportunity Structures . . . 77
4.6.5 Time Series Analysis . . . 78
4.7 Results . . . 80
4.7.1 Time Series Analysis Results . . . 80
4.7.2 Comparison between categories of rape myths . . . 84
4.7.3 Geographic Proximity: Individuals . . . 85
4.7.4 Robustness Checks: Substantive Labeling . . . 88
4.8 Conclusion . . . 90
4.9 Discussion . . . 91
4.10 Limitations and Future Work . . . 92

5 Article III: Digital Collective Memories of #MeToo 95
5.1 Introduction . . . 95
5.2 Background and Related Work . . . 97
5.2.1 Why Memory Matters . . . 97
5.2.2 Memory-Movement Nexus . . . 98
5.2.3 Digital Media . . . 99
5.3 Research Questions . . . 102
5.4 Data . . . 102
5.4.1 Archive: Harvard Schlesinger Library #MeToo Project . . . 102
5.4.2 Archive: Feminist and Queer Activist Movements in Transnational China and the Asian Diaspora . . . 105
5.4.3 TikTok . . . 108
5.4.4 YouTube . . . 109
5.4.5 Wikipedia . . . 110
5.5 Methods . . . 113
5.5.1 Procedure . . . 114
5.6 Results . . . 115
5.6.1 Curation . . . 115
5.6.2 Circulation . . . 122
5.6.3 Claims . . . 129

5.7 Conclusion and Discussion . . . 133
5.8 Limitations and Further Work . . . 136

6 Conclusion **137**
6.1 Contributions . . . 137
6.2 Limitations . . . 141
6.3 Concluding Remarks . . . 143
6.3.1 Ethics and Positionality . . . 144

References **147**

Appendices **167**

A Article I: Statistical Outputs **167**

B Article II **175**
B.1 Data Augmentation . . . 175
B.2 Media Enrichment . . . 175
B.3 Media Cloud Query . . . 176
B.4 Thresholds for Relevance and Substantive Rape Myth Classification . . . 176
B.5 Detected Peaks of Media Coverage about #MeToo . . . 176

C Subject: Collaboration with Hubert Au **179**

List of Figures

2.1 Defining Elements of Connective and Collective Action Networks . . . 15

3.1 Dialogic Framework of Diffusion . . . 28
3.2 Activity for 10 Protest Networks with the Highest Total Volume. . . . 33
3.3 Activity Plot of Hashtag Campaigns and Selected Time Periods . . . 35
3.4 Interactions Across Period 3 . . . 45
3.5 Awareness Counts in Agent-Based Simulations . . . 48
3.6 Experimentation Counts Against Experimentation Chance for Period 3. . . . 49
3.7 Distributions of Movement Application due to Secondary Diffusion in Model 6 . . . 49
3.8 Size Differences Between Simulated English #MeToo and Second-largest Networks . . . 52
3.9 Rank Correlations Between Simulated and Actual Data for Period 1 . . . 53
3.10 Rank Correlations Between Simulated and Actual Data for Period 2 . . . 54
3.11 Network of Interactions Between Protest Networks . . . 54

4.1 Enrichment Success Rate for Top 5 Languages . . . 71
4.2 Time Series Breakdown of Rape Myth Frequency in the U.S. . . . 81
4.3 Time Series Breakdown of Rape Myth Frequency in India . . . 81
4.4 Intervention Analysis for the U.S. . . . 82
4.5 Intervention Analysis for South Korea . . . 83
4.6 Relative Effect Sizes for Countries with Negative Intervention Effects . . . 83
4.7 Point Estimates for Coefficients of Political Openness . . . 84
4.8 Detected Rape Myths in Japanese Media . . . 85
4.9 Detected Rape Myths in U.K. Media . . . 86
4.10 Prevalence of Victimizing Perpetrators Myth in Articles about Harvey Weinstein . . . 87
4.11 Prevalence of Victimizing Perpetrators Myth in Articles about Harvey Weinstein in a Culturally Distant Context . . . 87
4.12 Prevalence of Victimizing Perpetrators Myth in Articles about Nana Patekar . . . 88
4.13 Prevalence of Victimizing Perpetrators Myth in Articles about Noriyuki Yamaguchi . . . 88

5.1 Distribution of Item Types in U.S. Collection . . . 103
5.2 Distribution of Capture Dates of Items in Harvard Schlesinger #MeToo Project . . . 104
5.3 Distribution of Item Types in China Collection . . . 106
5.4 Distribution of Capture Dates for Items in China Collection . . . 107
5.5 Distribution of Audio Languages in YouTube Dataset . . . 109
5.6 Distribution of Video Duration in the YouTube Dataset . . . 110
5.7 Example Article from Harvard Crimson in U.S. Collection . . . 116
5.8 Example Archived Reddit Thread . . . 118
5.9 Example Archived Homepage of an Advocacy Organization Red Maple (红枫) . . . 120
5.10 GitHub Repository Archiving Queer Acts in China . . . 121
5.11 Example of French TikTok User's Disclosure . . . 124
5.12 Example of Spanish TikTok User's Disclosure . . . 125

5.13 Example of Calls to Action 126
5.14 Example of Chronicling #MeToo History in South Korea on TikTok 127
5.15 Example of Podcast Type Movement Backlash 128
5.16 Example of Perpetuation of Myths 129
5.17 'Awareness and empathy' Subsection in English #MeToo Movement Wikipedia Page 130
5.18 Italian #MeToo Page 132

B.1 Enrichment Success Rate 176
B.2 Hashtags Used in Media Cloud Query 177
B.3 Distribution of 'Rape Myth' Labels and their Logits. 177
B.4 Peaks of Coverage 178

List of Tables

1.1 Research Questions 8

3.1 Hashtags Used for Data Collection 34
3.2 Parameter Combination Ranges 48
3.3 Distribution of Agents across Primary Protest Networks 50
3.4 Distance-to-Data for Period 1 51
3.5 Distance-to-Data for Period 2 52
3.6 Distance-to-Data for Period 3 52

4.1 Table of Rape Myths 73
4.2 Fine-tuning Performance Metrics 80
4.3 Robustness Check 89

5.1 Blog Sources in the U.S. Collection 104
5.2 News Sources in the U.S. Collection 105

A.1 Generalized Linear Regression for Period 3: Activity, Forward Step-wise Search 167
A.2 Generalized Linear Regression for Period 3: Activity, Backward Step-wise Search 168
A.3 Generalized Linear Regression for Period 1: Activity, Step-wise Search 168
A.4 Generalized Linear Regression for Period 2: Activity, Step-wise Search 169
A.5 Generalized Linear Regression for Period 1: Interval, Step-wise Search 169
A.6 Generalized Linear Regression for Period 2: Interval, Step-wise Search 170
A.7 Generalized Linear Regression for Period 3: Interval, Step-wise Search 170
A.8 Generalized Linear Regression for Period 1: Cluster Change, Forward Step-wise Search . . . 171
A.9 Generalized Linear Regression for Period 1: Cluster Change, Backward Step-wise Search . . 171
A.10 Generalized Linear Regression for Period 2: Cluster Change, Forward Step-wise Search . . . 172
A.11 Generalized Linear Regression for Period 2: Cluster Change, Backward Step-wise Search . . 172
A.12 Generalized Linear Regression for Period 3: Cluster Change, Forward Step-wise Search . . . 173
A.13 Generalized Linear Regression for Period 3: Cluster Change, Backward Step-wise Search . . 174

Chapter 1

Introduction

1.1 Background and Rationale

In October, 2017 actress Alyssa Milano tweeted (Milano, 2017):

> If you've been sexually harassed or assaulted write 'me too' as a reply to this tweet.

The next day, Milano woke up to many millions of replies and retweets. Not long after, this outpouring of disclosures and accusations continued to build, going 'viral', catalyzing many conversations online and offline about sexual harassment and violence (Zacharek et al., 2017). Many survivors disclosed their accounts of sexual harassment and sexual assault, demonstrating the ubiquity of the problem. For others, #MeToo encouraged discussions about victim-blaming, rape myths, and rape culture (Loney-Howes et al., 2021). Digital platforms including Twitter, Facebook, and Instagram facilitated this opportunity to document experiences of sexual violence and evolved into a new way of 'speaking out' and to receive recognition, validation, and support (Serisier, 2018). This became the #MeToo movement, eventually reaching over 85 countries and having been translated to nearly as many languages (AFP, 2018; A. Park, 2017).

The #MeToo movement exists within a larger context of the digital activism of contemporary social movements: for example, the Arab Spring (2010), the Occupy Movement (2011), and Black Lives Matter (2012) (Gerbaudo, 2012; Howard & Hussain, 2013). It also sits within a larger context of feminist activism in which campaigns against sexual harassment and assault have often been central: feminists in the U.S. for example, declared the 'personal is political' in the 1970s to advance understanding that women's personal and private experience of violence were inseparable from their political oppression.

More recently, there has been an surge of feminist protests around the world that has gained widespread media attention and has been enabled by the development and penetration of social and digital technologies. This

digital feminist activism, understood as the use of digital platforms to 'dialogue, network, organize, and challenge' (Mendes et al., 2019, p.2), is the tradition in which #MeToo is also situated: 'cyberfeminism' was created in the 1990s (Tuzcu, 2016), *SlutWalk* (Mendes, 2015), #GirlsLikeUs (2012), #YesAllWomen (2014), #BringBackOurGirls (2014), #WhyIStayed (2014), #YouOKSis (2014-2015), and #EverydaySexism (2015) are some examples. After #MeToo in 2017, campaigns such as #LetHerSpeak have continued digital feminist efforts (Tickell, 2022). Moreover, the phrase 'me too' as a phrase to foster a space where survivors could speak out and find support originated over a decade before Milano's tweet, beginning with Tarana Burke's Me Too movement in 2006. #MeToo is just one of the latest campaigns confronting rape culture, building upon the efforts of previous initiatives that aimed to bring visibility to this issue and inspire societal transformation.

Where #MeToo stands out is that it remains the most enduring instance of feminist activism in recent years, entering into the everyday lexicon on sexual violence in many different countries and political contexts. More than half a decade since Milano's tweet, discussions and news reports on cases of sexual harassment and assault continue to be associated with #MeToo (Kantor & Twohey, 2022). This evolving legacy may be for a variety of reasons, not limited to the explicitly sexist remarks of then US Presidential candidate Trump, the high-profile public figures like Harvey Weinstein who made many headlines and was subsequently convicted, and the pithy individual-focused phrasing of the hashtag allowing for a more inviting space for survivors. #MeToo stands as a unique instance of digital feminist activism.

Unlike much digital feminist activism that preceded it, #MeToo—though originating on Twitter, a U.S.-based platform and in English—spread to many countries around the world. Google dedicated a web page to the visualization of searches globally on their platform for #MeToo through 'Me Too Rising' (Google, 2019). Many non-English equivalents of '#MeToo' emerged for particular countries. For example, #MoiAussi and #BalanceTonPorc developed in France (Lopez et al., 2019); #MiTu, # 我也是, and # 米兔 (a transliteration of the English, translating literally as 'Rice Bunny') appeared in China (Liao & Luqiu, 2022); #QuellaVoltaChe manifested in Italy (Blasi, 2019). It was also unique in the extent to which everyone speaking out could be heard through all the channels where #MeToo found purchase (Boyle, 2019a). This collective volume was and is critically important given the key role consciousness raising plays in feminist activism historically, but also because women's experiences have long been suppressed, excluded, or ignored in the public record (Serisier, 2018).

Further, it remains a relevant movement: a simple search of the hashtag on a number of platforms shows survivors are continuing to actively use it to disclose persistent cultures of sexual harassment and assault: for example, professional chess is contending with its '#MeToo moment' in 2023 (Robinson, 2023), and Taiwan is taking up a 'wave' of #MeToo (Chien, 2023). The movement has contributed to a media environment in which

survivors are more empowered to make public accusations, continuing to make headlines and shape discussion at the highest levels of public scrutiny.

There is a growing body of scholarly work examining the ways social media platforms and digital technology more broadly have enabled contemporary activism, including digital feminist activism. #MeToo, like the other hashtag campaigns mentioned above, cannot be considered separately from the media platforms through which it has circulated Boyle, 2019a: #MeToo is an instance of *networked* activism, enabled by the affordances of the platforms upon which it circulates (Suk et al., 2023). Due to its reach and resonance within these platforms, #MeToo is also a mainstream news story–also disseminated increasingly on digital platforms–involving many voices vying against each other attempting to delineate, assert and limit or bound the meanings and significance of the outpouring of evidence of gendered violence and harassment associated with the hashtag. More emphatically, these voices are also therefore contending to define and delineate what even constitutes sexual violence (Heberle & Grace, 2009).

The role of digital technologies in social movements have prompted scholars to reconsider organizational structures of contemporary activism, beyond how they might facilitate traditional collective action offline protest (Olson, 1965). Earl and Kimport (2011) argued that digital infrastructures do not simply amplify existing activism, but fundamentally change how activism operates. Taking seriously the assumption that an older collective action model is insufficient to account for the emerging behaviors, Bennett and Segerberg (2013) subsequently developed the concept of *connective action*. In this framework, new digital media are conceptualized not as instrument but as context (Bimber, 2017): platforms can constitute organizations in their own right. Online media allow and encourage for cheaper and less formal organization. Digital technologies have facilitated the emergence of social movements from 'grassroots' where no specific organizations are present and leadership that speaks unanimously on behalf of the challengers no longer exists (S. J. Jackson et al., 2020; Jungherr et al., 2020; Margetts et al., 2016).

Theories of connective action are continuously evolving, and much remains to be learned from #MeToo: the unique transnational diffusion that happened through digital media such as Twitter, its impacts on public understandings of concepts like sexual harassment, assault, and violence, and longer term changes (e.g. Clark, 2015; Dixon, 2014; S. J. Jackson et al., 2020; Mendes et al., 2018; Trott, 2019). More work is required to examine the scale, reach, and seeming permanence the movement has gathered in its full international scope (Trott, 2020). Scholarship is often focused on the U.S. or the English-speaking world (Cuklanz, 2020; Gallagher et al., 2019; S. J. Jackson et al., 2019; Keplinger et al., 2019; Orgad & Gill, 2019; Xiong et al., 2019), examines individual case studies (Hindes & Fileborn, 2019; Larsen, 2018; Martini, 2020; Moricz, 2019; Mukherjee et al., 2023;

Reestorff, 2021; Zeng, 2020), or compares two countries (Hasunuma & Shin, 2019; Lopez et al., 2019). But the unique geographical reach #MeToo has had calls for more. Therefore, this doctoral project intends to complement foregoing work by asking: What was the effect of #MeToo on international discourse concerning sexual violence? The research questions to be posed are important not only to contribute to theoretical debates within scholarship, but to advance our practical understanding of how modern feminist campaigns can be conducted and how they can have meaningful impacts.

To consider the movement in its full international scope, new methodologies will be required. These methodologies must capture, understand, and analyze the digital footprint of #MeToo across languages, platforms, and time. They should draw from and operationalize theoretical concepts from social movement theory and feminist scholarship. For example, what methods can be applied to understand the spread of #MeToo across languages on Twitter under the paradigm of connective action (Bennett & Segerberg, 2013)? This thesis, therefore, seeks to combine social movement scholarship, feminist scholarship, and novel computational methods to answer the central research question.

This thesis comprises three standalone articles. This project will draw primarily from social movement literature, building upon theories of social movement diffusion, impact and relationship with news media, and the collective memory of movements.

Article I examines the determinants of the global diffusion of #MeToo, complementing and improving on previous work on diffusion in the following ways. Methodologically, previous work on the diffusion of #MeToo have typically considered only small periods of time insufficient to address the determinants of diffusion. Hassan et al. (2019a) and Gallagher et al. (2019) examine Twitter data between Oct 15-Oct 31, 2017. Other studies collected later sampled from Feb 01, 2019 to 31 Jul, 2019, and explicitly advocate for a longitudinal study as further work (Reyes-Menendez et al., 2020). Trott (2020) examines the first three days of tweets, Oct 15-Oct 17, 2017. Xiong et al. (2019) do not examine data later than 2018. Few studies have examined the movement's hashtag campaigns across multiple countries. M. Lee and Murdie (2021) explicitly examine the global diffusion of #MeToo, but limit their analysis to English-speaking #MeToo tweets, limiting the conclusions that can be drawn.

Yu et al. (2020) examine 33 countries in their analysis and offer the most comprehensive dataset, but like M. Lee and Murdie (2021) they equate the strength of the #MeToo movement in one country with the volume of Twitter activity. However, populations on Twitter have been well documented to not be representative of the wider population of a given country (Blank & Lutz, 2017).

Importantly, the mentioned works do not address the specific mechanisms of diffusion and how they apply to #MeToo. Article I seeks to contribute theoretically in this space. Yu et al. (2020) test the effect of structural affinity (Giugni et al., 1998) on diffusion. Notwithstanding the limitation of considering the volume of tweets as a metric of strength, this approach does not determine *how* spread occurs but rather whether the scale of participation can be explained by structural affinity. Both M. Lee and Murdie (2021) and Suk et al. (2023) employ similar approaches, with the latter using variational auto-regression between time series to imply influence.

Article I addresses all the following lacunae. By explicitly utilizing Chabot's (2010) framework of dialogue as a mechanism of relational diffusion (Tarrow, 2005), Article I gains an explanatory power that has not been sufficiently provided thus far. It also explains diffusive behavior across 36 languages over 3 years by examining user interaction and activity *outside* only their tweets containing '#MeToo', in contrast with the vast majority of previous work on digital and hashtag activism. The much more comprehensive data collection enables a more robust answer to the question of the determinants of mobilization. By design, Article I does not assume a higher tweet volume in one country or language indicates a greater movement strength, but seeks only to explain the effect of dialogue on the spread of support for #MeToo across languages. Article I finds that dialogue–and therefore relational diffusion–can explain a large degree of the transnational diffusion of #MeToo. Theoretically, this demonstrates the importance of relational diffusion in contrast to non-relational diffusion (for example, news reports) and mediated diffusion (brokered connections between people).

Moreover, this is achieved through developing novel methodologies. The article develops a novel agent-based modeling approach, where each part of the dialogue model of diffusion (Chabot, 2010) is explicitly operationalized, allowing a robust test of the influence of dialogue for #MeToo.

Article II examines the influence of #MeToo on the representation of sexual violence in the media in 47 countries around the world. Rape myths–generalized and false beliefs about sexual assault that trivialize a sexual assault or suggest that a sexual assault did not occur (Franiuk, Seefelt, & Vandello, 2008)–are an important part of how sexual violence is represented and occur regularly, solidify patriarchal ideas and the idea of a 'just world'that dictates good things happen to good people and bad things happen to bad people (Lerner, 1980). Widespread acceptance of rape myths is a perennial problem, and their appearance in news media serve to reinforce the public acceptance for them, which consequently not only shapes the very definition of sexual violence (Heberle & Grace, 2009), but acceptance of rape myths has an impact on an individual's likelihood of committing sexual assault (Bohner et al., 2005; Lanier, 2001). Therefore understanding how #MeToo has had an influence on rape myths as a movement transcending borders is important.

Previous work on media representations of sexual assault in relation to #MeToo have predominantly been small-

scale and qualitative: Article II seeks to complement previous work by expanding the scope of examination. Typically, studies in this context have centered around a number of high profile cases associated with #MeToo. Hindes and Fileborn (2019), for example, examine media framing around the case of comedian Aziz Ansari as covered in Australian news outlets. Hindes and Fileborn (2019) and Cuklanz (2020) examined a small corpus of articles from *The Washington Post* and *The New York Times*. Orgad and Gill (2019) examines Uma Thurman's case solely. A few studies considered the cross-national scope of #MeToo. Askanius and Hartley (2019) compared news framing of #MeToo stories across Denmark and Sweden.

What studies up to this point have lacked is a measure of how #MeToo has impacted, if at all, the presence of rape myths in news and therefore representations of sexual violence, globally. Scholars have therefore further been unable to test how theorized factors such as political opportunity structures and geographic proximity affect this outcome of the movement. Article II makes this theoretical contribution, finding that whilst consistent with previous work that have found little effect caused by the movement (Boyle & Rathnayake, 2020; Cuklanz, 2020; Hindes & Fileborn, 2019), political opportunity structures and geographic proximity did not explain the variations between where #MeToo had an impact and where it did not (McCurdy, 2012). Countries with less media controls, media centralization, and higher women's empowerment were *not* more likely to improve their representations of sexual violence, indicating just how universal and entrenched patriarchal ideas are.

Article II additionally contributes methodologically in the use of language-agnostic models (Feng et al., 2022) in concert with careful human annotation drawing from rape myths identified by feminist scholars (Brownmiller, 1975; Burt, 1980) to achieve a wide multilingual analysis.

Together, Articles I and II demonstrate that despite the global lack of support for the movement in the media even in countries with greater political openness, digital feminist activism can utilize the affordances of social media platforms to discuss, share, and ultimately diffuse and strengthen the movement across borders. Where previous work has found ways in which digital activism can mobilize online and offline mobilization in individual countries (De Choudhury et al., 2016; Freelon et al., 2018; Vasi & Suh, 2016) and has been able to build online communities and identities (S. J. Jackson & Foucault Welles, 2016; Reyes-Menendez et al., 2020), Article I offers an analysis of this mobilization and building of communities in the process of diffusion globally. Relational diffusion through dialogue, in contrast to non-relational and meditated diffusion, plays a critical role in social media spaces where individual activists may negotiate cross-national and cross-cultural interactions and differences that then constitute a transnational movement. Article II provides evidence of the reluctance of news outlets–of which many prominent ones are owned by figures complicit in perpetuating rape culture (Durham, 2021)–indicating just how universal and entrenched patriarchal practices are.

As attention moves on in social media platforms and as news cycles come and go, however, what will be the longer term effects and legacy of #MeToo? The 'success' of a movement can be an elusive idea (Gamson, 1990, p.28). Social movements are not homogeneous and it is therefore difficult to assign success or failure to an entire movement: this is especially true for transnational movements. Rather, Article III will conclude the thesis with a study focused on collective memory.

Social movements are intertwined with collective memories. The association of the civil rights movement in the U.S. with peaceful protest, for example, was a contingent fact: the formation of that collective memory of peacefulness was affected by the social movement at the time, and that collective memory influences how we remember and consider the movement today. Collective memory is a powerful cultural resource instrumental not only in ascribing value to past events and therefore to social movements, but also contribute to the building of future movement communities and influence public opinion (Kubal & Becerra, 2014).

Article III, therefore, examines how collective memory of #MeToo has crystallized in digital arenas where meaning is formed and contested. It explores the different ways in which digital archives and collective memory about #MeToo form and how factors such as geography, language, and political openness influence these constructions. Understanding how collective memory is formed and contested in digital feminist activism remains an under-explored area (Kubal & Becerra, 2014; Twyman et al., 2017). Three types of digital collective memories will be examined: curated ones, such as the Harvard Schlesinger Library's archive of #MeToo digital traces, user-contributed ('circulated') records of the movement on YouTube and TikTok, and consolidated 'claims' of the movement and associated events on Wikipedia articles across languages. The contrast between all three enables a glimpse into the digital collective memory-making about #MeToo, and perhaps indicate how future digitally-born movements may proceed when their mobilizations subside.

A summary of research questions posed is outlined in Table 1.1. Overall, this project has and will continue to contribute to theoretical social movement debates in the digital age and the development of novel network and language processing techniques to study such phenomena. Articles I and II have revealed that individuals are able to initiate across borders positive change and engagement in the discourse around sexual violence, whereas institutions regardless of media control and wider women's empowerment are much slower at adopting feminist perspectives if they do so at all. Article III demonstrates the variety and disjointedness across platforms of #MeToo collective memory that is continuously being produced, and re-emphasizes the need for individual activists to push to have their voices heard to escape the institutional boundaries of curations and encyclopedias. This thesis argues for the the importance of collective, individual contestation of memory and meaning making beyond the English-speaking world. Loney-Howes et al. (2021, p.13) emphasize the importance of 'establishing

a digital archive of feminist practices of resistance, we can begin to map, ... record and archive these initiatives so that the range of structural conditions enabling sexual violence are exposed and cannot be forgotten.' This project hopes to be part of that collective global effort.

1.2 Research Questions

Overall Question: What was the effect of #MeToo on international discourse concerning sexual violence?

Table 1.1

Research Questions

Article	Research Questions	Theoretical Framework	Data	Methods
I	What effect did dialogue between activists have on the transnational diffusion of frames in #MeToo activism on Twitter?	Dialogue model of transnational diffusion (Chabot, 2010)	Tweets containing #MeToo in a range of languages, and user timeline histories	Networks: Bi-spectral Clustering, Statistical Regression, Agent-based modeling
II	What was the impact of #MeToo on the presence and frequency of rape myths in news media around the world?	Dynamics between social movements and media coverage (McCurdy, 2012) in relation to rape myths (Boyle, 2019a; Burt, 1980), political opportunity and geographic proximity (Harlow et al., 2020; Koopmans, 2004).	Media articles	Qualitative Coding, Natural Language Processing, Bayesian Structural Time Series, Statistical Regression
III	How are has #MeToo lasted through digital memory?	Memory (Burkey, 2020; Merrill & Lindgren, 2020), collective memory of social movements (Pentzold, 2009; Twyman et al., 2017)	Wikipedia pages in all languages available for each page, along with edit histories. Curated archives of #MeToo. YouTube and TikTok data	Qualitative Discourse Analysis

1.3 Thesis Structure

This chapter is structured as follows. As the thesis is presented in an integrated and not monograph manner, each subsequent chapter is also a standalone article.

The thesis proceeds as follows.

In **Chapter 2: Literature Review**, I lay the foundation of the social movement theory that underpins and links all three articles, outlining the shift from collective action to connective action. This chapter then addresses the need to expand connective action theories drawing from three areas of social movement theory of diffusion, representation in media, and collective memory that each of Articles I-III speak to. The chapter further discusses the landscape of literature on the #MeToo movement specifically, and where the lacunae to which this thesis hopes to contribute are.

In **Chapter 3: The Transnational and Multilingual Diffusion of #MeToo (Article I)**, the global diffusion of #MeToo through Twitter is studied by operationalizing a dialogical framework of diffusion developed by Chabot (2010). This study goes beyond previous studies, being longitudinal over 3 years and spanning 36 languages and known versions of '#MeToo'. I use agent-based modeling to demonstrate a new way to operationalize the theoretical frameworks and how it may be applied to online platforms, potentially beyond Twitter in future work.

An adapted version of article I is currently under review at Sage Open.

In **Chapter 4: The Effect of #MeToo on Rape Myths in the Media: A Global Multi-lingual Analysis (Article II)**, I conduct a multilingual analysis of media across 47 countries of the frequency of rape myths occurring in the media, determining how #MeToo in these countries have played a significant role in changing the frequency of these rape myths. This analysis employs a supervised computational approach, classifying rape myths drawn from feminist scholars (Burt, 1980).

An adapted version of Article II was submitted to ICWSM 2024.

In **Chapter 5: The Formation of Digital Collective Memories of #MeToo (Article III)**, I examine a third aspect of the digital dynamics of modern social movements. Collective memories of social movements–and indeed more generally–are powerful cultural resources that shape public opinion, alter institutional action, and contribute to current and future social movements. Moreover, social movements themselves are intertwined with the construction of collective memories. For digital activism, these collective memories can take various forms, and critically can be contributed to directly by activists. In this article, therefore, I explore the different ways in which digital archives and collective memory about #MeToo forms. I examine three types of digital collective memories: curated, such as the Harvard Schlesinger Library's archive of #MeToo digital traces, user-contributed records of the movement on TikTok and YouTube, and associated events on Wikipedia articles across languages.

An adapted version of Article III will be submitted to Internet Histories.

In **Chapter 6: Conclusions and Discussion**, I restate the empirical findings and theoretical advances of the project, which boil down to three sets of broader contributions and avenues for related future work.

Chapter 2

Literature Review

This literature review will be structured into two main sections. First in Section 2.1, I will review the development of scholarship on social movements from its early research to modern theories of digitally mediated movements. Second, in Section 2.2, work specifically on #MeToo is reviewed and the need for a global scope and approach to match #MeToo's international reach is argued for. Each chapter individually attends to the literature and related work relevant for its specific context and argument. Therefore, this chapter will address the background literature underpinning and relating to all chapters, or any literature to be discussed that does not belong to any individual empirical chapter.

This thesis draws primarily from social movement theory, so I will begin there. This chapter will commence by delineating the traditional conception of collective action and its limitations in addressing contemporary developments in social and digital technology. It underscores several challenges that conventional collective action theory has faced, including the issue of free riders, and discusses how the widespread availability of digital technology has brought about a shift that helps alleviate this problem. It establishes an understanding of why new theories such as *connective action* are needed to illuminate technologically-facilitated activism. Further, it will address some ways in which connective action theory has overlooked feminist movements. This is the background within which all subsequent literature is situated.

Thereafter, the chapter will argue that although the role of digital technologies in social movements has correctly prompted scholars to reconsider how social movements can and do operate in tandem with social media or personal sharing networks, traditional news media and collective memory are still critical parts of modern social movements and should be foregrounded alongside the hyper-connectivity and new modes of individual participation emphasized by the connective action model. Traditional media plays a critical role for wider broadcasting, adoption, and framing. Similarly, how movements are remembered determines not only their legacy and success, but also how those movements can influence future activism. These form the basis of Articles II

and III, respectively. Article II therefore additionally draws a theoretical basis from feminist scholarship on the representation of sexual assault in media. Article III, similarly, draws on memory studies.

This chapter will argue that, as mentioned in the introduction, existing work within the paradigm of connective action and in social movement research has yet to fully match the international scope of #MeToo. If indeed we are to speak of #MeToo as a 'global' phenomenon, then associated scholarship should also exhibit matching scope and methodology. To capture and address some of this global reach, this thesis combines the theoretical backdrop of social movement theory with computational methodology. The latter parts of this chapter are therefore dedicated to an overview of some of these methodological strands of research.

2.1 Social Movements

2.1.1 Collective Action

The field of modern social movements research began to develop seriously as an arena of study in the mid-20th century through the study of movements, often with fascism in mind (Kornhauser, 1968). Therefore, the questions typically focused on understanding why radical movements would occur in otherwise well-functioning democracies (Meyer, 2004). The waves of protest movements in the 1960s in the US and other Western democracies sparked a reexamining of the foregoing precepts on social movements (Della Porta & Diani, 2020). Scholars began to understand activists and movement participants as actors making rational choices to improve disadvantaged positions in society (McCarthy & Zald, 1977; Piven & Cloward, 1979). The key questions began to shift from *why* to *how* about the collective action of social movements: focus on the processes by which movement actors gather and mobilize activities such as protests.

Olson (1965) demonstrated, however, the *free rider* problem of collective action. He invited us to imagine some collective action, perhaps to propose new legislation on climate change. For an actor considering joining the collective, the rational calculus runs as follows. If the collective action succeeds without the person's involvement, then they have reaped the social rewards without any expenditure. If the collective action fails, no time is wasted. The potential participant is pushed towards not participating, towards being a *free rider*. This analysis concludes that collective action should not occur often, if at all. Collective action *does* occur, of course. It is on the basis of the free rider problem that Olson (1965) theorizes the importance of a social movement organization. In this model, social movement organizations are necessary to facilitate and advance the goals of a group.

Since then, much work has centered around the social movement organization (henceforth SMO). Tradition-

ally, SMOs were understood as formal groups that sought to mobilize a constituent group against a defined antagonist (Gamson, 1990; McCarthy & Zald, 1977). As the study of social movements developed, the formality of SMO structure in theory and in actual practice has not gone unchallenged. Most notably, feminist movements have long made a point of *structurelessness* (Kesselman et al., 2007). This point is returned to in the next section.

Nevertheless, scholars have constructed definitions of social movements on the coordinating functions SMOs serve (e.g. Diani, 1992), arguing that contentious performances rely on the organized mobilization of an aggrieved group (Tilly, 2008; Tilly & Tarrow, 2015). Organizations coalesce collective identities, and collective identities were a critical factor in leveraging social networks for movement recruitment (Gould, 1991, 2003; S. K. Han, 2009; Jasper & Poulsen, 1995; Snow et al., 1980). McCarthy and Zald proffered four characteristics of SMOs: leadership, a small membership, speaking for a constituency (the aggrieved group), and the targeting of policy (Zald & McCarthy, 1987, p.375).

An important part of the traditional conception of SMOs, then, is that of leadership. The facilitation SMOs provide is substantially diminished without key figures holding a relatively small membership together, speaking for the challenging group, and debating counter-movements. Numerous studies have upheld the importance of leadership in both traditional social movements and online, digitally mediated social movements (Gerbaudo, 2012; Melucci, 1996). Various social movement schools of thought such as resource mobilization theory (McCarthy & Zald, 1977) and new social movements (Melucci, 1989; Touraine, 1977) have conceptualized the importance of leadership in different ways, from gathering and maintaining resources to decision making and framing strategies (Snow & Benford, 1992; Zald, 1996).

A movement such as #MeToo, however, poses significant challenges to both the importance of leadership and the formality of organizations as a core precept of social movements. Feminist movements have long resisted leadership and hierarchy, and recent digital technologies have arguably enabled fundamentally new structural forms. We turn to those now.

2.1.2 Structurelessness in Feminist Movements

Feminist movements have had a long history around the world, but have been most researched and theorized in the U.S. context where the scholarship on social movements developed. In particular, the women's liberation movement of the 1960s and 1970s in the U.S. was concurrent with the development of much traditional social movement scholarship. The women's liberation movement sought equal rights and greater personal freedoms, and in line with the framework of the theories mentioned above (McCarthy & Zald, 1977; Melucci, 1989;

Touraine, 1977), movement efforts led to the establishment of organizations such as the National Organization for Women (NOW). NOW had formal offices, budget, meetings, and small membership in comparison to the women it represented. NOW also had influential and charismatic leaders like Betty Friedan, author of *The Feminine Mystique* (Friedan, 1965).

Women's liberation movements of the time raised important practices of feminist activism that remain influential today (Trott, 2019). Amongst the more 'radical' groups of feminists, structurelessness became a key precept, intended to empower every participant with equal voice and equal authority. An intense egalitarianism was developed, deliberately moving away from bureaucratic organization of SMOs such as NOW. Structurelessness prescribed a looseness and informality that actively encourages participation and against hierarchical leadership because hierarchical leadership instantiates precisely the types of oppressive structures feminist collectives were rallied against (Freeman, 1969; Kesselman et al., 2007). This is the first challenge to the traditional understanding of SMOs.

Notably, Freeman (1972) famously pushed back on the possibility of pure structurelessness. She argued that it was just the attempts towards structurelessness that caused elitism within feminist groups: without the constraints of formal roles, the veneer of informality and looseness can mask the power dynamics that inevitably arise in a social group. She thought that structure was ineluctable, though it can be flexible and change over time. For the present purposes no adjudication is required on the issue of structurelessness itself. Instead, it is important to underscore the importance of alternate structures. A growing body of work has demonstrated how structurelessness has remained salient (Banet-Weiser & Miltner, 2016; Horeck, 2014; S. J. Jackson et al., 2020; Trott, 2019, 2020). #MeToo is no exception. In order to understand the second set of issues with the traditional collective action model, the next section will consider theories of connective action.

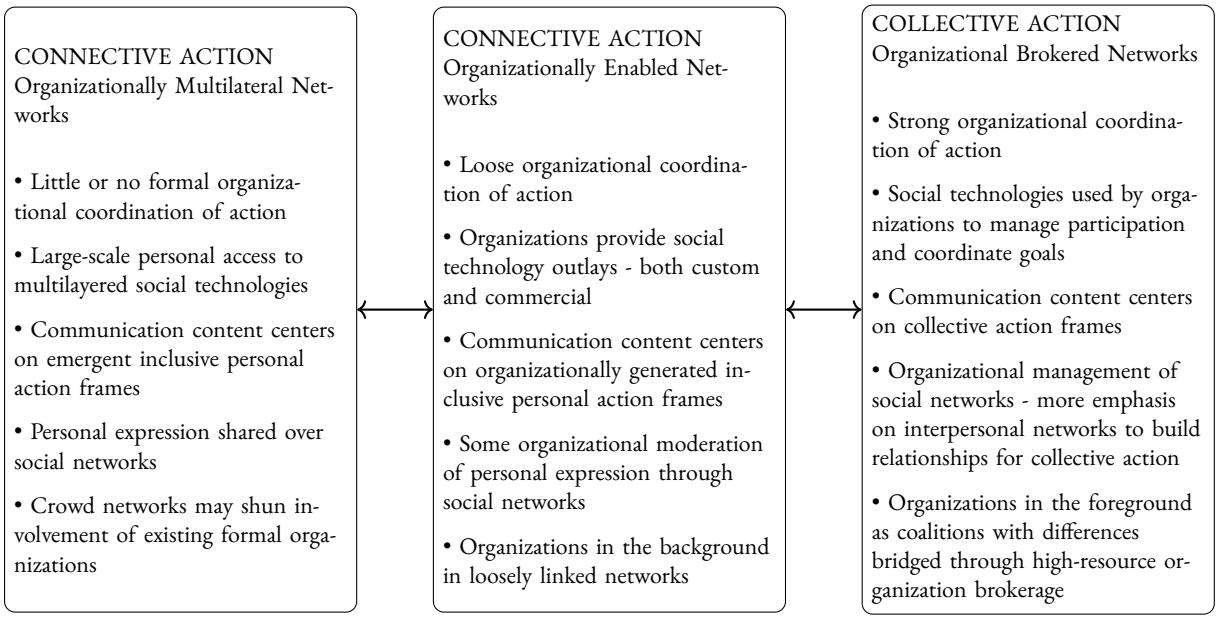
2.1.3 Digital Media and Connective Action

The proliferation of social and digital technologies has drastically lowered coordination costs and has facilitated new modes of organization. Consequently, a number of scholars have argued that these new modes of interaction, facilitation, and organization demanded a new framework of understanding. Technologies personalize online content, providing individuals reasons for protesting a situation they seek to change across the platforms available. Earl and Kimport (2011) argued that digital infrastructures do not simply amplify existing activism, but fundamentally change how activism operates. Therefore, the collective action model is insufficient to account for emerging behaviors. Where collective action is associated with high degrees of centralized organizational resources and action that formed collective identities, numerous cases have emerged where per-

sonalized collective action formations are created where digital media is indispensable (Bennett & Segerberg, 2013). Bennett and Segerberg (2013) subsequently developed a framework they named *connective action*. In this framework, new digital media are conceptualized not as instrument but as context (Bimber, 2017): platforms can constitute organizations in their own right. Bimber et al. (2005) contend that online media allow and encourage for cheaper and less formal organization. As evidence of this, scholars have found that in contemporary movements like the Arab Spring, traditional forms of organization and leadership played a relatively minor role (Azer et al., 2019; Poell et al., 2016). Digital technologies have facilitated the emergence of social movements from 'grassroots' where no specific organizations are present and leadership that speaks unanimously on behalf of the challengers no longer exists (S. J. Jackson et al., 2020; Jungherr et al., 2020; Margetts et al., 2016).

Figure 2.1

Defining Elements of Connective and Collective Action Networks



Note. Adapted from Bennett and Segerberg (2013, p.47).

Figure 2.1 shows the connective action typologies in relation to collective action. Keeping the traditional collective action theory as their rightmost and first organizational category, Bennett and Segerberg (2013) do not believe that connective action completely replaces traditional or pre-internet activism. Organizationally brokered protests, in their parlance, maintain a traditional, hierarchical structure and are driven by established formal organizations which create, facilitate, and maintain a unified collective. Although this category of activism existed before the digital media causing the exercise in reimagining, the traditional nature of collective activism does not preclude it incorporating digital technologies if used, for example, for cost-saving and efficient means of coordinating and messaging, as long as the digital technologies used do not constitute 'organizational

infrastructure' that characterizes the connective action categories.

The left two categories of activism are the new logics of connective action proposed. The central category of 'organizationally enabled networks' may be considered a hybrid of the more traditional collective action and the crowd-enabled organizational network. This middle-ground consists of organizations sponsoring actions as in traditional collective action, but allow for and create opportunities and invitations for followers to personalize their own engagement. In doing so, they bridge the gap to the fully 'connective' form of action. Formal groups are considered simply another connection in the network. This adaptability and personalization allows better appeals to a wider range of participants and potential recruits.

Finally, at the opposite extreme from traditional collective action sits crowd-enabled connective action or self-organizing networks. Under this paradigm, media platforms themselves act as organizational hubs in lieu of any particular formal organization or group. A crowd-enabled connective network is characterized by personalized action frames. Critically, these are easily adaptable and individualized by a wide variety of participants. Individuals can then take part however suits them best: they may adapt the overall movement's message in whatever way resonates with their own personal experiences and beliefs. Notably, a sufficient volume of these personalized participatory actions can lead to a change in the overall movement's message, or certainly how it is perceived by non-participants and observers. This property of connective action will be important in both Articles I and III. Participating individuals additionally are not required to prescribe to the aggregate suite of claims, beliefs, and ideological ideas that others in the movement might share. Crowd-enabled action networks mainly consist of organizations that are not membership-based and individuals who are not closely connected to established groups or may not align closely with them. Leadership is not centralized, and in fact an intentional 'relative absence of purposeful association, boundedness, and core actors' (Bennett & Segerberg, 2013, p.89). The onus of organization is shifted onto the digital platforms themselves, where traditional boundaries between networks–and for current interests across borders–is theorized to be more fluid.

Theories of connective action are continuously evolving and have not escaped criticism. Karpf (2014) argued that focusing purely on the visible, online aspects of a movement fails to capture still important offline modes of participation. Trott (2019) argued that Bennett and Segerberg's (2013) analysis is too restricted to movements that have clear economic goal, or are centered around protest with a defined legislative agenda to enact. This applies in particular to feminist movements–and therefore to #MeToo–where at least in the US context it neither has a clear economic goal nor with a singular legislative goal. The same is true of how is it discussed in retrospect beyond the English-speaking world, as I argue in Article III. Further, whilst it is certainly true as Bennett and Segerberg (2013) argue that new forms of digital organization have lowered the bar for engage-

ment, this is tempered by the emotional and personal costs that are often not accounted for in criticisms of 'slacktivism' (Harlow & Guo, 2014). It becomes more imperative to account for such costs in the context of a movement concerning sexual violence where participants regularly make disclosures. Many factors can impact whether a survivor decides to disclose their experiences, and especially when the person disclosing is publicly recognizable, they often become targets of media attention and heightened public scrutiny (Trott, 2018). Such targeted backlash is often sexist and racialized (Citron, 2014).

2.1.4 Feminist Digital Activism

The unique informality, non-hierarchy, and striving towards structurelessness that has been characteristic of feminist activism, in combination with shift from collective action to connective action, collide to produce the rich characteristics and processes of modern feminist digital activism. Throughout the past decade and more, feminist protests have gained significant coverage that has been enabled by the connective tissue of new social and digital technologies (S. J. Jackson et al., 2020; Keller et al., 2018). For example, the *Hollaback!* blog was inspired by the spreading of a photograph taken on a mobile phone of a man masturbating in front of a woman in a New York City subway. Later, in 2011, Slutwalk was a march organized through the use of social media and digital technologies in response to a Canadian police officer who suggested that women should avoid 'dressing like sluts' (Mendes, 2015). The same technologies also allowed the international spread of the Slutwalk narrative. More recently, Twitter has been a particularly powerful site where movements can spark. With the now normalized use of a hashtag to indicate shared interest and as a way of sifting through a massive amount of information, the hashtag has become the *lingua franca* of connective action developed on Twitter (S. J. Jackson et al., 2020). Feminist activists have made active use of this *lingua franca*: as mentioned in the Introduction, #GirlsLikeUs (2012), #YesAllWomen (2014), #WhyIStayed (2014), #YouOKSis (2014-2015), and #EverydaySexism (2015) are all recent examples. They have all fostered collective identity in ways not dissimilar to that of SMOs (de Almeida, 2019; S. J. Jackson et al., 2020; Mendes et al., 2018). #MeToo inherits both elements of structurelessness and connective action.

2.1.5 Broadening Connective Action Paradigm: Diffusion, Media, and Collective Memory

Much more may be said about the challenges and responses to the conceptualization of connective action: Chadwick (2017), for example, mounts an important criticism, asserting that a connective or collective typology can be restrictive of understanding, and suggests the importance of hybridity: a contemporary repertoire of contentious politics that shifts between online and offline spaces. However, this thesis does not seek to comment directly on these debates in the scholarship. Rather, it begins where most scholars agree: political organization

and digital activism more broadly now incorporate diverse mobilizing methods, and where #MeToo is indeed situated. In this mode, online and offline acts are intermingled so that local and national communities are involved. However, where much of the preceding discussions center around the organizational logics of protest organizations of various kinds and ranging in informality and connective tissue, this thesis broadens the scope of analysis beyond individual activists, incorporating three other dimensions also from social movement scholarship that are not only relevant for #MeToo as a social movement in the first instance, but perhaps also linking and expanding this connective action paradigm to these other areas of social movement theory.

These are: diffusion, traditional media, and collective memory. Each contribute to the overall picture of #MeToo globally and as an instance of connective action. The first links most directly to Bennett and Segerberg's (2013) categorization of connective action. If indeed #MeToo is a global movement in a unique and noteworthy way as an instance of digital activism (Boyle, 2019a; S. J. Jackson et al., 2020), and it is theorized that digital media was is the organizational tissue underpinning crowd-enabled networks, just *how*, *how much*, and indeed *whether* this connectivity gave rise to these transnational connections is nontrivial. Such inquiry belongs to the realm of diffusion within social movement scholarship, and therefore Article I asks how theories of diffusion understood in the in the collective action paradigm may be applied and updated in a setting of connective action.

The second is the relationship between traditional news media and social movements. Whether collective or connective, social movements are not limited to digital platforms that have the affordances with the capacity for crowd-enabled personalized action frames to be expressed (Davis & Chouinard, 2016). It is well-documented how unrepresentative of wider populations social media platforms are (Blank & Lutz, 2017). If the digital dynamics of social movement are to be properly understood, especially in an increasingly digital journalistic landscape, how traditional media interacts with movements, particularly of a leaderless nature, reveals much about the reach, reaction, and impact a movement has. Again, in this regard, #MeToo serves as a prime example to examine across political contexts.

Finally, where attention is naturally drawn to highly visible organizational patterns of connective action on media platforms, mobilizations never last forever. Where digital platforms enable these new forms of mobilization and activism, they also archive indiscriminately and totally: everything can be archived in one way or another. Some part of these records will form the collective memory of #MeToo across the world. Even before the internet, how movements are remembered is highly nontrivial, contingent, and important for not only for their own legacy but for the success of future movements with similar goals (Whitlinger, 2021). Further, the intersection of scholarship between memory studies and social movements remains an underdeveloped area, especially in relation to digital media (Daphi & Zamponi, 2019; Hoskins, 2018b; Zamponi, 2013).

As mentioned earlier in this chapter, each article on diffusion, media, and collective memory go into further depth on each area of scholarship. The remainder of this chapter now turns to scholarship that examines the #MeToo movement specifically. Given the reach of the movement and the wide interest from various areas of scholarship, not necessarily within the social movement research strand, they are organized below.

2.2 Related Work on #MeToo

This section groups the scholarship by themes explored in the research, through which the the lacunae of international comparisons and analyses that this thesis tackles will be illustrated. As with the theoretical frameworks above, where further detail is relevant to a particular article comprising this thesis, it will be discussed again in further detail within that chapter.

2.2.1 The Role of Organizations

Unsurprisingly, few works have centered organizations, especially social movement organizations, in their analysis. Only one study has explicitly considered the role of social movement organizations (SMOs) in their analysis (Xiong et al., 2019). Xiong et al. (2019) examined how SMOs in the US framed messages and positioned themselves within #MeToo on Twitter in the first few months of the movement in the U.S. They find six main themes of hashtags used amongst SMOs to position themselves within the movement: related issues, action-oriented hashtags, event-specific hashtags, references to victims, and activist mentions. Though their analysis demonstrates a commitment and adaptation of SMOs consistent with organizationally enabled networks under the typology discussed above in Figure 2.1, their analysis does not claim a centrality of SMOs to the protest network on Twitter. More importantly for the present purposes, little is known about what role SMOs might have played beyond the U.S., and therefore limits what conclusions may be made about the role of organizations in #MeToo more holistically.

2.2.2 Participation

Much work has also naturally centered on participatory motivations and processes. As is expected of connective action with personalized action frames, the reasons for participation are varied. Sometimes, when these personalized action frames are testimonies or disclosures of suvivorship, their delivery online contributes to a sense of power, especially for survivors whose stories are regularly marginalized or minimized (Trott, 2019). For others, it was the connection that one had ('me') to the experiences of others ('too') (Boyle, 2019a). Solidarity was a major driver of participatory volume in early campaign in the U.S. in 'network-level reciprocal disclosures' (Gallagher et al., 2019): the hashtag was the facilitator allowing this expression.

Generally, though, much of this scholarship draws upon Twitter or social media data from the U.S.: Brunner and Partlow-Lefevre (2020) are another example, finding networked conscious-raising efforts but limited to U.S.. Trott (2020) performed a similar analysis of #MeToo in English. Twitter studies using English tweets are as plentiful as they are insightful (e.g. Boyd & McEwan, 2022; Boyle, 2019a; M. Lee & Murdie, 2021; Mendes et al., 2018; Nutbeam & Mereish, 2022; Pandey et al., 2018; Reyes-Menendez et al., 2020; Siuta et al., 2023; Tatz, 2021). The same is true even beyond Twitter as the main platform of interest: on YouTube, Harrington and Gerrard (2023) investigate English-tagged #MeToo by women micro-influencers, and Manikonda et al. (2018), one of the few to examine Reddit, also employed a matching scope of analysis.

Consistently, however, the study of participation and visibility within #MeToo's networked feminism highlights a lack of intersectionality: #MeToo for whom? Trott (2020) calls for feminist researchers to be mindful of the voices that are excluded when examining popular feminist activism. Perspectives on participation are so noticeably skewed (Horeck, 2023) commented on the 'celebrity #MeToo documentary' specifically within the U.S. Sometimes, these calls for greater intersectionality, or an identification of skewed demographics of participation revolve around the English-speaking Twitter networks (Mueller et al., 2021). In line with Flaskerud (2019) and Lukose (2018), however, who emphasize the importance of understanding the nuances of participation and the different cultural landscape and binds in which survivors must operate, a body of work has emerged engaging with particular cultural and geopolitical contexts and how they impinge upon #MeToo participation. For example, caste plays a unique role in India, and the leadership of Modi is different from that embodied by Trump and Biden. These calls are reinforced by analyses of why Japanese women have for several cultural reasons felt a disconnect between themselves and the #MeToo movement (Miura, 2021; Mizoroki et al., 2023). The same 'culturally inappropriate' nature of the movement often hindered Bangladeshi women from participating (Hassan et al., 2019b). In South Korea, deep patriarchal societal structures have instead given rise in some instances to more combative feminism such as the 4B movement alongside #MeToo (J. Lee & Jeong, 2021), and 'troll' feminist activism (Jeong, 2020; Mendes & Jeong, 2023; S. Park, 2024). In the Chinese context there exists an additional dimension of censorship (Fu et al., 2013), which prompted a variety of counter-censorship measures such as developing phonetic equivalents of 'me too' in Chinese ('米兔' literally meaning 'rice bunny'). Feminist activists employed emojis of rice bowls and rabbits to circumvent state censorship (L. Han & Liu, 2023; Zeng, 2020). Also examining the Chinese context, Lin and Yang (2019) identified the 'non-responsive society, the traditional culture, as well as the powerful people who are in control that oppress vulnerable people into marginal conditions' (2019, p.846), preserving the silence of survivors with disabilities.

This body of scholarship clearly reveals that participatory dynamics–certainly beyond #MeToo as well–are ev-

idently complex, context-specific, and individual-specific. When considering the totality of #MeToo global participatory dynamics, we wish to be able to draw conclusions of the sort made using English and U.S. focused studies, but with the scope beyond individual country and language analyses, all whilst respecting the limitations of drawing conclusions about a 'global' movement with data from a selection of countries. Some of the limitations in scope of work mentioned here are naturally due to the timing of #MeToo across the world, where it was not possible to conduct such analyses: for example, Taiwan has recently been experiencing their #MeToo wave of activism (Chien, 2023). It is in this space this thesis positions itself, in complement to the body of work described.

2.2.3 Comparative Scholarship

Naturally, there is also a body of scholarship examining international and cross-country comparisons of #MeToo, to which I now turn. Where such scholarship is directly relevant to a particular article in this thesis, a fuller, detailed discussion of it will be left to that article. This section will argue that such work–that this thesis hopes to contribute–remains an underdeveloped area of literature.

Only a few studies compare hashtag campaigns across countries. Lopez et al. (2019) do so for the French #BalanceTonPorc and English #MeToo, for example. Belotti et al. (2023) conduct a simlar comparison between #NiUnaMenos in Latin America with English #MeToo, explaining similarities and differences in the forms of violence against women highlighted in the two campaigns through the very different socio-cultural contexts that nevertheless are able to share a common sense of vulnerability attached to being a woman in patriarchal societies. Hasunuma and Shin (2019) examined the progression of #MeToo throughout Japan and South Korea. The authors note that of #MeToo in South Korea had a higher impact, where public prosecutor Suh Ji-Hyeon who spoke out explicitly stated that the US movement, and Tarana Burke's work in particular, played a significant role in her decision to speak out. The authors theorize that the recent activism against femicide and hidden camera abuse in South Korea provided a riper space for women to speak out when #MeToo arrived. By contrast, they argued that #MeToo was less prominent in Japan because of a cultural focus on group harmony, meaning that speaking of sexual assault and harassment is much more forbidden.

Four research projects have explicitly examined the diffusive behavior and patterns of #MeToo. M. Lee and Murdie (2021) and Yu et al. (2020) take the broadest international scope, assessing the impact of political openness and structural affinity on the strength of the movement across countries (Giugni, 1998). Suk et al. (2023) look particularly at English, Spanish, and Korean diffusion, utilizing correlation patterns between time series of tweet volumes to as a measure of diffusion. Yu et al. (2022) examine the spread of #MeToo to the 16Days cam-

paign. The 16Days campaign is an annual international campaign sponsored by the United Nations General Secretary and organized by UN Women. Critically, none of the four mentioned works operationalize a specific *mechanism* of diffusion. That is what Article I hopes to achieve, and these are all discussed in further detail within Article I.

Others have not focused on individual, but rather have examined media representations of the movement and sexual violence across countries. Starkey et al. (2019) examine the U.S., Japan, Australia, and India through a thematic analysis. Askanius and Hartley (2019) reveal a consistent framing of sexual assault as a personal problem, even in countries like Denmark and Sweden, where gender equality is a legislative goal. This body of work, while insightful, is limited by its focus on individual cases, specific news sources, or singular geographic locations. There is a noted gap in the literature regarding the international treatment of #MeToo media coverage, suggesting a need for a broader quantitative study to understand the global impact of the movement and the role of traditional media in shaping attitudes towards sexual assault and violence. This scholarship is further addressed in Article II, where a novel methodology is applied to expand the range of countries and languages examined, with a particular focus on the use of rape myths within media reports (Burt, 1980).

Finally, Levy and Mattsson (2020) investigated the effect of #MeToo across 30 OECD countries on the reports of sexual crimes reported to the police, finding that the movement increased such reporting by 10%[1].

This thesis hopes to expand, therefore, on these comparisons in both the scope of analysis as well as the methodologies employed in conducting those analyses. This chapter concludes with a discussion on these existing methodologies.

2.2.4 Computational Approaches

Scholars have employed a range of natural language processing (NLP) techniques to study #MeToo. A popular sociolinguistic tool for analysis has been Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2015), a well-established psycholinguistic lexicon. Widely utilised in human-computer interaction (HCI) research and computer supported cooperative work (CSCW) research, and has been used for researching online discourse including that of #MeToo. Rho et al. (2018) used LIWC to characterize the linguistic affect and style across comments on Facebook pages belonging to three media outlets: *DemNow*, *Breitbart*, and the *The New York Times*. Hassan et al. (2019) used the biological process (body, sexual) and drives (power, risk, reward) LIWC categories to infer how vivid a disclosure is and what motivation an author has in creating a tweet containing '#MeToo'. Lopez et al. (2019) used it to infer affect, cognitive attributes, and linguistic style to examine how

[1] though that still means reports of sexual crimes remains severely under-reported, and that the legal systems in many OECD countries are not set up for survivors (Maquin, 2020)

people frame their meaning via semantic exchange. Notably, Lopez et al. (2019) conducted a cross-lingual analysis employing a French LIWC (Piolat et al., 2011). Foster (2019) used LIWC to examine correlation between linguistic markers of gender identity and linguistic markers of wellbeing. Pandey et al. (2018) developed a machine learning (convolutional neural network) classifier for a tweet intent typology and subsequently employed LIWC to infer further linguistic insight into each category. Finally, Manikonda et al. (2018) use LIWC to measure and compare the differences between types of emotions expressed between Reddit and Twitter.

Though LIWC is advantageous in reducing a researchers' idiosyncratic tendencies and biases as compared to other forms of content and thematic analysis, the associations between individual words and the assigned categories in LIWC requires corroboration with explicit measures. More concretely, as the dictionary was created with no specific domain of application, the application of it to different forms of speech should be validated (Pennebaker et al., 2015). LIWC's categorisation of female words to indicate strong alignment with the female gender may hold more true in longer form text than on a microblogging service like Twitter, say (Foster, 2019). None of the foregoing studies perform such explicit validation. The need for such external corroboration is made clear by the variety of domains to which LIWC was applied within discourses connected to #MeToo. Further, for research questions to be posed, LIWC is not foreseen to be a useful tool.

Other studies have employed deep learning techniques for feature extraction and modeling. Khatua et al. (2018) applied deep learning to determine a scale of assault seriousness in different places from tweets containing '#MeToo': at home, at educational institutions, or in public spaces. They experiment between model types including a multilayer perceptron (MLP), convolutional neural network (CNN), long short-term memory (LSTM) and bidirectional LSTM (Bi-LSTM). Field et al. (2019) introduce a novel methodology that generates an entity-centric score for objects mentioned in news articles to assign power, agency, and sentiment as determined by the text. Their method draws from manual labeling of power, agency, and sentiment to transitive verbs (e.g. 'Alice pushed Bob') from psychology (Rashkin et al., 2016; Sap et al., 2017) and uses context-aware word embeddings (mathematical vector representations of words in natural language) to generate an analysis of news media articles on #MeToo. Their methodology is detailed in greater depth in Article II.

Network analysis has been another common methodology in the study of #MeToo. Trott (2020) examined the early retweet and mention network of #MeToo in the first few days after Milano's initial tweet, performing community detection on the protest network to determine which accounts were most closely tied to each other. Xiong et al. (2019), discussed above in 2.2.1, construct an 'ego-centered network of feminism'. Gallagher et al. (2019) consider the follower network of users who used the #MeToo hashtag to determine whether exposure to a disclosure from someone they were following made a user more likely to disclose themselves. Martini (2020)

examined the nature of counter-movements in the German protest network. However, studies employing network analyses have all examined #MeToo networks in one country.

Although such computational methods described have enabled the 'Big Data' analysis of a number of aspects of #MeToo, for the research questions posed on diffusion processes and the analysis of media coverage in a range of languages, the application of more recently developed and still ongoing methodologies are required.

2.3 Conclusion: Transnational Social Movements

This chapter has laid out the background history and key points of social movement theory upon which the rest of this thesis is built. The shift from collective action to connective action was demanded by the advent of digital technologies. This thesis contributes to the expansion to theories of connective action by examining diffusion, media, and collective memory as areas of social movement scholarship in application to a unique modern instance of connective action. Further, existing scholarship on #MeToo is often centered on the U.S. and the English-speaking world more broadly. This thesis contributes in expanding that focus and developing new methodologies to do so.

Chapter 3

Article I: The Transnational and Multilingual Diffusion of #MeToo

3.1 Introduction

Social movement scholars broadly agree that the social networking sites, and the internet more generally, allow movements to distribute information and engage with very large audiences (Earl, 2010; Earl & Kimport, 2011). More detailed mapping and analysis of the mechanisms by which such diffusion occurs and how these interact with offline protest, however, is still nascent. This paper considers the case study of the #MeToo movement that took hold in at least 85 countries (A. Park, 2017) and has been relevant in activism against sexual assault and violence since. Though having begun as Tarana Burke's 'Me Too' movement, the #MeToo movement has gathered international spread and resonance that requires its own recognition. Taking a theory of dialogue developed by Chabot (2010) for the diffusion of social movements, this study asks whether Twitter has served not only as a communication channel but as a diffusive mechanism for #MeToo movements.

3.2 Motivation and Contribution

This study seeks to test Chabot's (2010) theorized process of dialogue and its constituent processes that enable transnational diffusion, built on Tarrow's (2005) work, both of which are described in the following sections.

This study complements previous work on diffusion in the following ways. First, it contributes in its longitudinal design and scope. Previous work on the diffusion of #MeToo have typically considered only small periods of time insufficient to address the determinants of diffusion. Hassan et al. (2019a) and Gallagher et al. (2019) examine Twitter data between Oct 15-Oct 31, 2017. Other studies collected later sampled from Feb 01, 2019

to 31 Jul, 2019, and explicitly advocate for a longitudinal study as further work (Reyes-Menendez et al., 2020). Trott (2020) examines the first three days of tweets, Oct 15-Oct 17, 2017. Xiong et al. (2019) do not examine data later than 2018. Few studies have examined the movement's hashtag campaigns across multiple countries. M. Lee and Murdie (2021) explicitly examine the global diffusion of #MeToo, but on English-speaking #MeToo tweets. This work examines dynamics and mechanisms of diffusion for #MeToo across countries, for which a longitudinal design is necessary. This study explains diffusive behavior across 36 languages over 3 years.

Second, this study address the specific mechanisms of diffusion and how they apply to #MeToo, not offered by previous work. Yu et al. (2020) test the effect of structural affinity (Giugni et al., 1998) on diffusion, M. Lee and Murdie (2021) explain the tweet volumes by country in terms of political opportunity variables, and Suk et al. (2023) employ variational auto-regression between time series to imply influence between countries. Where this literature has left open, however, is a test of the theoretical mechanism that underpins the diffusion: previous approaches have not determined *how* spread occurs but rather whether the resultant scale of participation can be explained by other variables. Yu et al. (2022) do apply a causal model, but seek to explain the diffusion from English #MeToo to the 16 Days Campaign, a campaign organized by UN Women.

Moreover, though Yu et al. (2020) examine 33 countries in their analysis and offer the most comprehensive dataset of diffusion, but like M. Lee and Murdie (2021) and Suk et al. (2023) they equate the strength of the #MeToo movement in one country with the volume of Twitter activity. Populations on Twitter have been well documented to not be representative of the wider population of a given country (Blank & Lutz, 2017). This study uses volume of Twitter activity as the direct result of diffusive activity, but does not connect a dependency from that to strength.

Third, this investigation goes beyond the typical depth of data collection in studying digital activism. The direct utilization of a theoretical mechanism of diffusion (Chabot, 2010) requires analysis of regular tweets of a user *in addition to* their tweets containing '#MeToo'. The much more comprehensive data collection enables a more robust answer to the question of the determinants of mobilization.

Finally, this study contributes methodologically through the operationalization of each part of Chabot's (2010) theory. Two major methodological approaches were employed to triangulate answers to the research questions. First, a statistical analysis using time-aggregated measures of dialogue. This approach leveraged a recently developed user-language network clustering designed to identify activist interaction and therefore dialogue (Joseph et al., 2020). The use of this clustering has been hitherto restricted to networks of users and hashtags of interest; this paper extends the methodology beyond consideration of hashtags to phrases. Second was a set of agent-based models operationalizing individual aspects of 'dialogue' in order to observe dialogue at an indi-

vidual level. The agent-based modeling demonstrates not only that the theory of dialogue *can* be adapted and ported onto the mechanisms of Twitter and therefore possibly other online platforms according to different affordances, but also that the methodology is able to reproduce empirical results to a high degree of accuracy. These reproductions also demonstrate that only a limited set of parameters can powerfully simulate theoretical mechanisms in empirical social science. Further, this study also developed a number of evaluative measures to apply to agent-based models in this domain.

3.3 The Diffusion of Social Movements

It is commonly agreed that social movement 'diffuse' or 'spread'. That is, that innovation is passed between members of a social system (McAdam et al., 2001). Sometimes innovations spread across a country, or indeed *between* countries. It is difficult to understand movements' expansion and interaction with the public arena without understanding diffusion. A few key questions arise.

First, what spreads? Tactics, frames, issues, and symbols are all elements that may spread (Givan et al., 2010). These elements are either behavioral, such as sit-ins or protests, or ideational. The latter is of primary interest here. Ideational elements include collective action frames that define issues, goals, and targets. A frame, used in everyday discourse as it is in scholarly work, refers to interpretive schema with which simplifies, condenses, and codifies what is 'out there' in the world. Frames have been understood as important for the actualization of social movements in the collective action model, discussed in the previous section (Snow & Benford, 1992; Snow et al., 1986). Through strategic framing, social movements are engaged in the continued production and struggle over meaning (Snow & Benford, 1992, p.136).

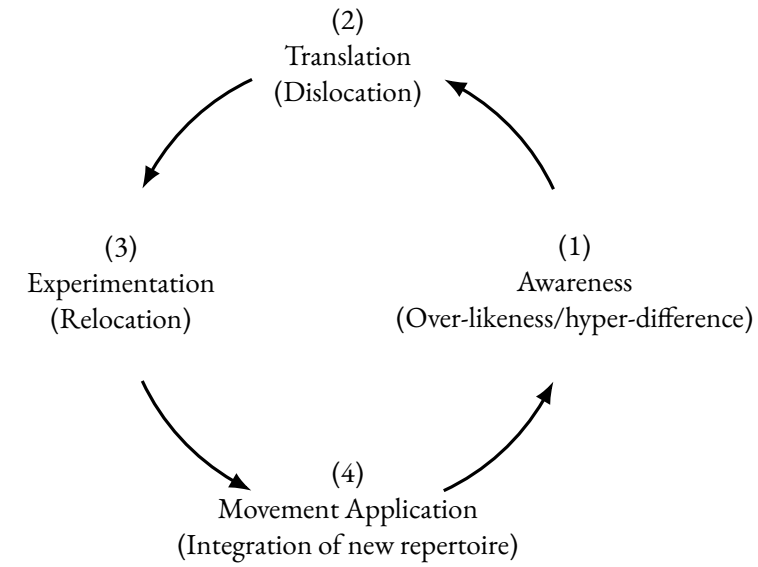
Second, what are the mechanisms and processes by which diffusion occurs? Just as the substance of what is diffused is multiple and varied, so are the processes by which diffusion occurs. For example, Singer (1970) studied mass media's role in the diffusion process. Soule (1997) and Gould (1991; 2003) queried the role of networks in the diffusion of protest repertoires and the growth of collective action. It is the processes of diffusion that will be of primary interest in this paper.

3.3.1 The Mechanisms of Diffusion

Tarrow (2005) put forth an authoritative analysis of transnational movement diffusion. He theorized three processes of diffusion: relational, non-relational, and mediated. Relational diffusion occurs along existing social ties. He argues that diffusion is often very social, where repertoires or frames are transmitted through avenues such as shared organizations, direct connections, or associational networks. Non-relational diffusion occurs

Figure 3.1

Dialogic Framework of Diffusion



Note. Adapted from Chabot (2010, p.106).

between people who have few or no social ties but who may consume media reports, for example. Mediated diffusion is brokerage: where clusters of movement participants and potential participants are separated but linked through a common third party connection (González-Bailón & Wang, 2016; Gould, 1991, 2003; Granovetter, 1973; Strang & Meyer, 1993).

For all pathways of diffusion, Tarrow emphasizes the importance of communication channels, enabling actors to understand similarities, theorize, and connect through brokers. Tarrow also argues that through the availability of digital connective platforms these processes are greatly accelerated (Tarrow, 2005).

The mere presence of increased connectivity and quicker communications, though, guarantees little about the spread of knowledge and innovation actually occurring. Though diffusion may occur through identifiable mechanisms and means, it is not mechanical (Givan et al., 2010, p.3). The pathway and the characteristics of diffusion cases are shaped through creative and strategic processes. Protest tactics and interpretive schema necessarily need to be applicable in the new geopolitical context in which they are used, and often only applied through adaptation and some re-imagining.

On this basis Chabot (2010) challenges Tarrow: more is required to understand the kind of interactions and processes that build towards diffusion. Chabot contends that activists potentially adopting innovations from overseas require the ability to ask questions, forge new relationships of trust, and adjudicate which aspects of existing practice or innovation can be transported into their political context. Dialogue—pedagogical, com-

municative, and relational—involves two or more active actors who are willing to share viewpoints, challenge ideologies, and power structures. Successful transnational diffusion between social movements is rare and difficult.

Chabot (2010) posits four interrelated processes that characterize dialogue: awareness, translation, experimentation, and movement application. Awareness indicates a potential movement participant or receiver of diffusion being cognizant of contentious political practices elsewhere. Translation is the meaningful exchange between practitioners and potential receivers on the relevance of some object of diffusion outside the original context. Perhaps the core aspect of dialogue, it is where receivers adopt existing frames, strategies, or practices. Experimentation indicates the receiver's usage of the object of diffusion in some small-scale application, and movement application is the final and most difficult part of dialogue, expanding small-scale applications into fully fledged and sustained practices and movements (Roggeband, 2010).

This study tests the theoretical framework for diffusion that is hypothesized to occur within digital communication channels. The basis for this study is that the #MeToo movement took hold in many countries on Twitter as a site where activists may interact and have dialogue, leading to transnational diffusion. The #MeToo movement took hold on Twitter across many countries, and Twitter is exactly the type of communication channel that accelerates diffusion processes and dialogue may occur between activists to facilitate such diffusion.

3.3.2 Diffusion and Feminist Movements

Diffusion scholars have explicitly studied these processes for feminist movements. Roggeband (2010) provides a notable study on the diffusion of frames in movements against sexual harassment, transitioning from American movements to a European context. Challenges arose where, for example, French press styled the American movements as 'American excess'. Through dialogue with American activists, French activists were able to find more effective framing. Parallels to what Roggeband (2010) found may be identified within #MeToo. Framing devices appear in the translations of the '#MeToo' hashtag. For example, the French #BalanceTonPorc meaning something akin to 'snitch on your pig' was the predominant hashtag associated with the movement. The Italian version of #MeToo became '#QuellaVoltaChe', translating as 'that time when'. In Chinese, the direct translation # 我也是 generated traction on Weibo. Subsequently, due to censorship after accusations were leveled against a prominent TV anchor Zhu Jun (朱軍) Chinese activists took to homophones and emojis (Zeng, 2020). In particular, 米兔 ('Rice Bunny') appeared as a homophone of '#MeToo'. Communicable through emojis, this circumvented censorship.

Specifically on the transnational diffusion of #MeToo. Yu et al. (2020) operationalized the volume of Twitter

activity in a given country as a measure of diffusion. The authors call on Giugni's (1998) theory of *structural affinity*, which claims that the presence of similar political structures across nations explains similarities of movements across political contexts. Immediately, the theoretical setup of their study raises a number of questions. First, though Giugni (1998) mentions both structural affinity and diffusion in the essay Yu et al. (2020) draw from, structural affinity is not introduced by Giugni as an explanation of diffusion, but rather a candidate model to explain the similarity of social movements across nations that often resemble each other. Second, supposing the use of structural affinity as an explanatory variable for diffusion were sufficient, no account of a mechanism is proposed. That is, supposing that countries with affinities along appropriate axes did indeed demonstrate diffusion of social movements, what would be the mechanism by which these similarities increase diffusion? Finally, though Yu et al. (2020) provide a brief discussion of diffusion, they do little to justify why *this* conception and operationalization of diffusion is informative. Indeed, Giugni (1998) quotes in the essay they cite: 'the real challenge is not so much in demonstrating the mere fact of diffusion... but to investigate systematically the conditions under which diffusion is likely to occur and the means by which it does.' (McAdam & Rucht, 1993)

Likewise, M. Lee and Murdie (2021) argue that political opportunity is important factor in the international diffusion of #MeToo. This work departs from theirs in two important ways: first, the scope of the present data collection intentionally reaches further than the English-speaking #MeToo networks, as called for by Lee and Murdie, and second, it is relational diffusion mechanisms that are specifically under examination in this work rather than other factors such as political opportunity.

3.4 Limitations of Twitter as a Diffusive Medium

Where aforementioned theory has suggested that the increased availability of communication channels like Twitter should facilitate transnational diffusion (Tarrow, 2005), there are some reasons to think otherwise both in the specific context of Twitter and of feminist movements.

First, Twitter–like other social networking sites–simultaneously creates a space that is critical for social movements and connective action that #MeToo is an example of (Brunner & Partlow-Lefevre, 2020; Zeng, 2020), but also allows for the occurrence of ample harassment, especially of women. Women who express feminist views are especially maligned and targeted with hate speech, death threats, and doxxing, just to name a few (Vera-Gray, 2017). #MeToo was particularly remarkable in the sheer volume of personal disclosures of sexual violence, perhaps in spite of these truths (Boyle, 2019a).

Second, Twitter's character limit on each individual tweet has been found to be potentially inhibiting of infor-

mation exchange between activists (Andalibi et al., 2018; Massanari, 2017; Penney & Dadas, 2014). Tweets are designed with brevity in mind as a push towards quick circulation, emphasizing timeliness over reflectiveness (Sheridan et al., 2012). Though this brevity helps account for some of the horizontal nature of other movements such as Occupy Wall Street, it may actively work against the construction of the dialogical framework in question here, which presupposes that dialogue as part of diffusion should emphasize just the opposite: length over brevity, reflectiveness over timeliness.

Third, Twitter simultaneously affords the desired visibility and the possibility of being surveilled and possibly censored by a for-profit social media platform. Visibility also means law enforcement has been documented monitoring protesters tweets (Penney & Dadas, 2014). Such suppression, or perceived suppression, may severely dampen any diffusion effects, as a potential receiver of diffusion may not be able to participate in protest networks in the same way as they might have without censorship surveillance effects. These factors affect activists and potential activists to different degrees in different political contexts, which could limit the dialogue and therefore diffusive effects on Twitter.

For all of these reasons, diffusion across languages and countries may not be as evident as theoretically posited by social movement scholars.

3.5 Research Questions and Hypotheses

Given the foregoing, the following research questions are posed:

1. What effect did dialogue between users on Twitter have on the transnational movement application of #MeToo hashtags in different languages?

2. Which, if any, protest networks experienced greater or lesser dialogical transnational diffusion through Twitter?

3.5.1 Hypotheses

Relational diffusion is known to occur, and Chabot (2010) gives the example of the dialogical framework in action with the diffusion of nonviolent protest tactics through Howard Thurman's interactions with Gandhi. To determine whether the same occurs on Twitter, two hypotheses are posited regarding **RQ1**. First, is there evidence for dialogue having an effect on movement application when examined at a higher level, where indicators are time-aggregated before and after critical events? Recognizing potential limitations of Twitter as a diffusive medium, the inevitable loss of some signal in any averaging, and that the temporal development of dialogue

should matter to its effect on diffusion:

(H1a) Dialogue, time-aggregated, has no effect on movement application.

Accounting for the individual interactions and the development of dialogue across time, however, the effect of the dialogic process should become more apparent:

(H1b) Dialogue is positively related to movement application.

Though #MeToo has has reached many countries, little is known about the paths it took to get there. Did the movement spread predominantly in a 'broadcast' type pattern with English #MeToo as the primary transmitter and other languages as receivers (Goel et al., 2016)? That there is little knowledge on the matter highlights a common limitation of current research in computational social science that focuses on the English-speaking world. It would make sense, for example, for networks in Chinese, Japanese, and Korean to engage meaningful dialogue and diffusive patterns in addition to receiving any diffusive effects from English. Goel et al. (2016) develop a measure that describes precisely the two ranges of behaviors and further interpolates between them: the *structural virality* $\nu(T)$ of a diffusion tree T, defined below, is low ($\nu(T) \approx 2$) when diffusion occurs through a single, large broadcast and is maximized when diffusion grows through multiple generations with any one node directly responsible for only a fraction of the total adoption. For a broadcast-type diffusion pattern, the shortest path between most nodes is through the node originating the broadcast, hence an average of approximately 2. At the other extreme, structural virality will approximately equal the height of the tree, equivalent to the depth of the deepest node from the origin.

$$\nu(T) = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1}^{N} d_{ij} \tag{3.1}$$

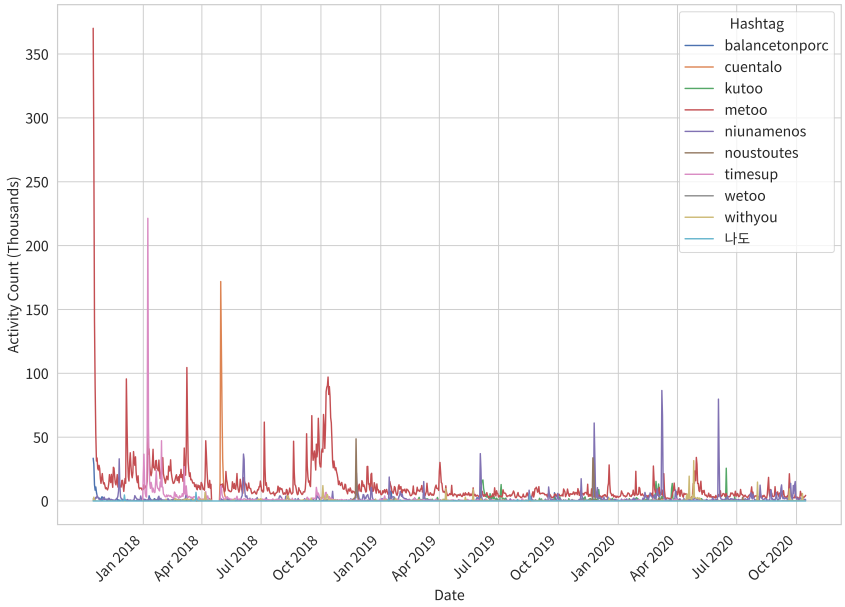
where N is the number of nodes, and d_{ij} denotes the shortest path between nodes i and j.

Additionally, another measure may be used to capture quantitatively the influence between languages. If it were the case the English #MeToo was the predominant diffusive originator, the network would mostly contain edges from English to other nodes, and hence a number of edges in the network that is approximately $(N-1)$. A network with frequent diffusion between other languages would have between $(N-1)$ and $\frac{N(N-1)}{2}$ edges, which is the total number of possible language pairs in the network. This is often called the density of a network. Using both these measures:

(H2) Dialogue is a process that occurs globally, and therefore English-speaking #MeToo networks are not the dominant influence on other protest networks. Structural virality $v(T)$ in the network

Figure 3.2

Activity for 10 Protest Networks with the Highest Total Volume.



should be significantly higher than 2, and density should be significantly higher than $(N - 1)$.

3.6 Data

3.6.1 Data collection

Data collection was conducted in two stages. To examine whether dialogue, however measured, had an impact on diffusion, the timelines of users who participated in at least one version of #MeToo were collected.

First, on a seed list shown in Table 3.1 of 36 known versions of #MeToo around the world, tweets using at least one of these were collected between 16 October 2017 and 16 October 2020. Hashtags were selected through a combination of recognition and reference to them in scholarly articles and newspaper articles (Chenou & Cepeda-Másmela, 2019; Hasunuma & Shin, 2019; Miura, 2021; Suk et al., 2023; Walsh, 2020; Zeng, 2020). Though smaller, more specific hashtags were in circulation for particular communities or industries–such as #MeTooSTEM (Camilleri, 2020)–higher-level hashtags were used as these remained the central ones referred back to and used more in transnational diffusion. These hashtags and their corresponding languages serve as proxies for international diffusion, rather than country-level. Though not ideal, determining tweet and user location remains highly unreliable (Zheng et al., 2018).

Figure 3.2 shows how #MeToo campaigns rose variously over the three-year period. A standard signal detection method was used to extract periods of time with the greatest peak strength across the largest number of hashtags,

Table 3.1

Hashtags Used for Data Collection

metoo	niunamenos
timesup	kutoo
cuentalo	withyou
balancetonporc	noustoutes
wetoo	나도
moiaussi	yotambien
quellavoltache	sendeanlat
ricebunny	私も
enazeda	我也是
woyeshi	memyös
jotambe	米兔
niere	stilleforopptak
نه_یعنی_نه	myharveyweinstein
gamani	ятоже
anakaman	nårmusikkenstilner
ונחנאסג	tôicũngvậy
watashimo	nårdansenstopper
나도당했다	نامك انأو

Note. Hashtags are presented in descending order, from top left to bottom right, based on the volume of collected tweets containing each respective hashtag.

where a peak was defined as having at least 5% the highest value, a prominence of 0.9, and a scanning width of 28 days. Prominence is the fraction of the range between the minimum and maximum values for a value to be considered a peak. The scanning width is how large a temporal window on each side of a peak to include when determining prominence. A visualization of the periods identified are in Figure 3.3. Hereafter, 'protest network' will be used to refer to the network of tweets corresponding to a particular hashtag.

Three periods were identified as key periods to collect (inclusive):

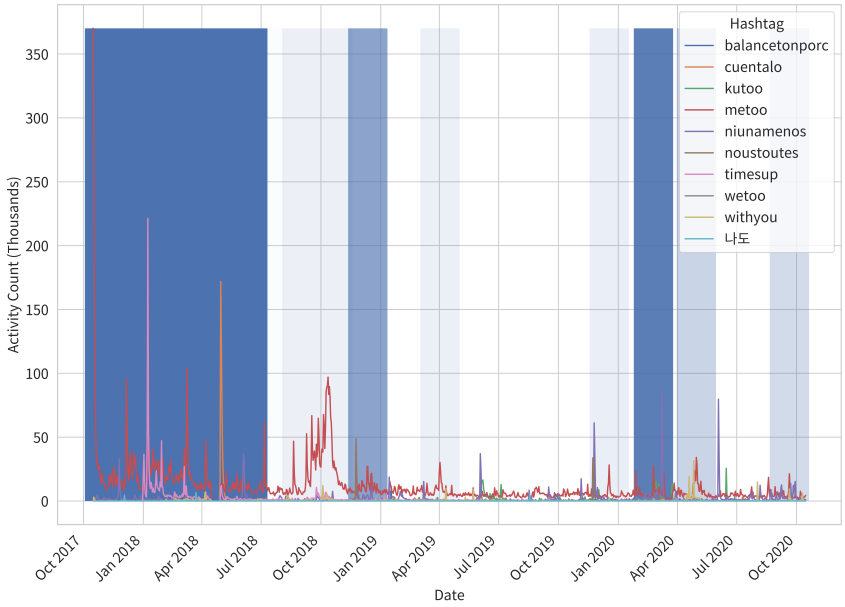
1. From 15 October 2017 to 29 May 2018
2. From 21 November 2018 to 2 January 2019
3. From 3 February 2020 to 16 March 2020

For each respective period, all tweets were collected of users who participated in a protest network at least once during this period. Retweets were not collected, however, as retweets represent perhaps an *awareness* but not necessarily an exchange between users that qualifies as dialogue (Chabot, 2010). To stay within API limits, a maximum number of tweets per user was imposed.

The sampling methods for the second part of the data collection on timelines, however, differed between the

Figure 3.3

Activity Plot of Hashtag Campaigns and Selected Time Periods



Note. Higher opacity indicates a higher collective peak intensity. The three selected periods are the three periods of highest opacity, i.e. of darkest shading.

groups. For the first and longest group, the most active users in the protest networks had their timelines collected. The other two groups were collected through a snowball sampling method: an initial random sample of 2,500 users from the full set of users in a group. This collected timeline data allows the determination of users (still within the full set of users who have participated in the protest networks) who have interacted with these users. Subsequently, another random sample of 2,500 users from this set are selected. Their timelines were collected and the process repeated. Five snowball samples comprised the final dataset collected for the second group and four snowball samples comprised the final dataset collected for the third. In total, the first group had 4344 users (from 2,488,905 participants), the second group had 12,586 users (from 564,058 participants), and the third had 9,796 users (from 664,970 participants). This difference in sampling methods allows the addressing of multiple possible scenarios: if transnational diffusion is dependent on having large numbers of interactions and activity to be visible, for example, then the sampling method for the first group would address this. Conversely, if dialogue leading to diffusion occurs only very rarely then more interactions are required. Then the sampling method for the second and third group would address this. Moreover, a sampling method that does not weight sampling likelihood by tweet volume is favorable in that it allows the measurement of the effect of dialogue on diffusion for users who are less prolific and may have a smaller platform–which is central to what #MeToo meant for many survivors (Boyle, 2019a). This sampling method is also a method of addressing the inequalities present in much existing work in computational work generally, but particularly in the growing

field of interdisciplinary computational social science (D'Ignazio & Klein, 2020).

For all tweets, the data cleaning was further performed: tweet text was lower-cased, had URLs removed through a regular expression pattern, had any ellipses at the end due to API truncation removed, had any 'rt' indicating retweets removed, and regularized text into one line by removing newline characters.

The datasets were not cleaned through the removal of software robots, or 'bots' for short. The removal of bots is commonplace amongst computational social science, including analyses of digital feminist activist networks (e.g. Groggel et al., 2024). Bots have been found to spread low-credibility content, peddle misinformation and disinformation (Himelein-Wachowiak et al., 2021), and target users with large followings with mentions and replies (Shao et al., 2018). In particular, *Botometer* (Yang et al., 2020) is a the most well-maintained, commonly used public tool for this task. This was not used, however, for the following reasons.

First, though there is a common conception that bots are all spam or spread malware, many are benign, such as @big_ben_clock, an account that impersonates the Big Ben clock by tweeting the time every hour, or a company help-desk that automatically sends holding replies to customer tweets. That is, bots are not always malicious, and can be used by to a variety of ends. How 'bot-like' accounts appear varies significantly depending on when the question is asked (Yang et al., 2022). Second, *Botometer*, though popular and easy to use, is also not the only available credible tool for bot detection and removal (e.g. Kudugunta & Ferrara, 2018; Mazza et al., 2019; Santia et al., 2019). How a bot should be detected–whether through network properties, account activity and temporal patterns, or profile and tweet content–is ever changing and often unclear, especially when bots are constantly adapting.

Third, and more importantly, there is substantial doubt as to the reliability of automated bot detection tools. Gallwitz and Kreil (2022) point out that *Botometer*'s high rate of false positives has been illustrated for years: over 20% of UN Women accounts and 35% of German news agency 'dpa' are misclassified as bots.

Fouth, datasets for training bot detection are further often questionable. Keeping with the commonly used *Botometer*, it was trained using an openly accessible dataset containing 57,155 accounts labeled as 'bot' and 30,853 labeled as 'human' in 2019 (Yang et al., 2019). These accounts were sourced from various origins, and some of the labels appear to be dubious. Even ignoring the fact that there is no 'ground-truth' to the matter–that we do not know what the true correlation between labeled and actual bots are–the majority of the 'bot' accounts originate from a group of spam or promotional accounts dating back to the initial years of Twitter (2009–2010): given how rapidly Twitter user bases, features, and practices have changed since, it is at best unclear how useful these data are.

Finally, I argue that in this dataset specifically, the issue of bots significantly disrupting the answer to the research questions is low. Malicious bots may spread misinformation (Himelein-Wachowiak et al., 2021), automatically reply to or troll individuals with large followings Shao et al. (2018), but this would little affect the diffusive processes examined here. Even if accounts with large followings attracted significant bot attention, there is little incentive (and certainly *monetary* incentive) for bots to target, simulate, or disrupt individual dialogue across borders for #MeToo at a large enough scale. Any such activity would also be severely diminished outside of English.

In summary, an effective cleaning of bots may or may not have improved the results in this study, and the variance of results achieved given all the foregoing concerns was decided to be too great a risk to take.

3.7 Methods

A number of decisions had to be made in order to port the theory to the context of Twitter. We considered three major methodological approaches: statistical models, agent-based models, and social contagion models. The statistical models are employed for time-aggregate analysis to address **H1a** as to whether or not dialogue's effect on diffusion is observed at a time-aggregate level. Agent-based models allow the more granular analysis required for **H1b**. Social contagion models are not used though sometimes linked to diffusion effects, and so are also addressed in this section.

3.7.1 Statistical Models

To understand whether there is an aggregate signal of diffusion, a collective statistical method was applied.

3.7.1.1 Operationalizing Dialogue and Diffusion: Independent Variables

First, whereas existing literature discussed above has naturally focused on activists exchanging information and innovation diffusing between them, this study does not make distinctions between 'activists' and 'non-activists'. Such distinctions are sometimes straightforward to make, such as if a user has declared their 'activist' status and/or an affiliation with a social movement organization. However, often such measures are insufficiently accurate, and proper approach would have to involve a qualitative human coding. Not only is a qualitative coding distinction difficult on the scale of users sampled (over 25,000), the distinction between 'activists' and 'non-activists' should not be a distinction made in this study. Further, the exclusive distinction between the two categories may even be argued to contradict the properties of *connective action* as compared to collective action, where the former is partly characterised by precisely the ease of direct participation that undermines a

distinction between activist and non-activist (Bennett & Segerberg, 2013). Therefore this study only deals with users generally.

A meaningful distinction, however, is between organizations and individuals. Social movement organizations have been found to be participants in #MeToo protest networks in English (Xiong et al., 2019), so have not been omitted from the analysis. How they participate in protest networks differs from that of individuals (Trott, 2020), and in order to code Twitter users as either organizations or individuals a model trained for this purpose in previous work was used that was trained to infer demographic information about Twitter users (Z. Wang et al., 2019). The same model was used to infer whether a user is male or female, and to which age category they belong. This model has also been used in recent social movement scholarship (Barrie & Frey, 2021).

Second, a key characteristic of social networking sites, and Twitter in particular, is the possible frequency and volume of interaction (Boyle, 2019a; Hassan et al., 2019a). As one measure of dialogue, then, the total number of times a user interacts (i.e. quotes, replies to, or mentions) another participant of protest networks. As mentioned above, retweets, though accounting for a large volume of activity, is hypothesized here not to constitute *meaningful* dialogue between users and potential activists as theorized in existing literature.

Third, an important aspect of interactions constitutive of dialogue is reciprocity. Reciprocity is necessary not only to establish dialogue, but also to establish relational diffusion (Tarrow, 2005), which is the subject of study here. Reciprocity is operationalized as follows. For a given user A who has interacted at least once with user B, the number of reciprocal interactions of user B to user A is recorded as a percentage. These two foregoing aspects constitute two measure of the **translation** stage.

Fourth, to operationalize **experimentation** (Chabot, 2010) this study hypothesizes that a measure of feedback for a user when they employ the use of a new phrase picked up from the **translation** phase, for example, is the feedback mechanism Twitter allows of likes, quotes, or replies (Comunello et al., 2016). Therefore, the number of tweets a user has in a particular protest campaign that receives more likes significantly higher than is usual for that user is used as an independent variable. 'Significantly higher' is understood as two standard deviations above their arithmetic mean of likes.

Finally, to understand if there is a nonzero effect of translation, experimentation, and dialogue more generally, a comparison to a baseline must be established. To establish a baseline of how much a user is expected to tweet, their non-protest related activity is extracted as an independent variable, and users are statistically matched on this criterion.

3.7.1.2 Dependent Variables

As no previous work has ported this dialogical framework to Twitter before„ there is no established way to measure the movement application dimension of transnational diffusion. To account for this, three dependent variables were used to triangulate a result.

First, the most basic indicator of successful movement application as a result of dialogue is simply to participate more in the protest network that is the recipient of transnational diffusion. Therefore, the first dependent variable used in this study is the activity of a user in a protest network after dialogue with other users.

However, such a measure can be inadequate. It would, for example, present a false positive for a user who participated multiple times in a protest network but only long after a significant peak of activity, by which time the window for effect of diffusion to be felt may already have passed. Therefore, the second indicator of successful movement application was the interval between a peak of a protest network and the time that a user first participated in the protest network.

Third, the successful diffusion of the framing might be visible, though successful diffusion of 'movement application' through Twitter of a protest tactic such as a sit-in is not observable from the platform itself. For example, French and Dutch feminist activists learned ways to highlight acts as sexual harassment and even to use the term 'harassment' at all (Roggeband, 2010). Were this to occur online, one observable outcome might be a convergence of language: if such frame diffusion happened, the language patterns of transmitters and receivers should overlap more.

Overlap was measured using bi-spectral clustering (Joseph et al., 2020). In contrast to preceding methodologies bi-spectral clustering operates with full timelines of user activity, placing users in a broader discursive context and communities in which they interact. This clustering was applied to users in each sampled group of users before and after the peaks of each protest network, and the dependent variable was the percentage of users a user interacted with who were not previously in the same cluster as they were before a peak that were subsequently in the same cluster after a peak. This indicates a convergence in their language and therefore possible frames. Bi-spectral clustering first constructs a bipartite graph, a type of network where nodes of one type (e.g., people) are connected to nodes of another type (e.g., hashtags).

Joseph et al. (2020) connect users and hashtags, but the dialogical process of translation is not limited to hashtags. This work expands the content half of the bipartite network to include 3-grams and 4-grams in addition to hashtags. A frame, then, is operationalized as such short phrases or hashtags Givan et al. (2010).

3.7.1.3 Modeling

The unit of analysis is a user. The dataset used for final statistical analysis incorporates the features aforementioned in Dependent Variables for the interactions users had, for each protest network, before the most prominent peak in the data collection period.

Given the highly skewed nature of the data, generalized linear models were used for the statistical analysis. For activity and interval response variables, a negative binomial distribution was used. A Gaussian distribution was used for the cluster change response variable, as the range for that variable is [-1,1].

3.7.2 Social Contagion

Whereas diffusion as driven by dialogue is new as to be applied to digital media, the topic of diffusion is not in the field of computational social science. Numerous scholars have modeled so-called 'contagion' effects (For example, Alshaabi et al., 2021; Aral & Nicolaides, 2017; Crocamo et al., 2021; Ferrara & Yang, 2015; Iacopini et al., 2019; Mønsted et al., 2017). As its name suggests, contagion effects originated with disease modeling (Pastor-Satorras et al., 2015), where the model comprises individual persons are either healthy or infectious. It is assumed that transmission of disease occurs in pairwise interactions between healthy and infected individuals, and that a single exposure is sufficient to cause infection. Some models have included a 'recovered' section of the population that are immune to reinfection, at least for a time period.

The attraction of applying contagion models to social phenomena is apparent. It has been used to track the adoption of norms, the behaviors or new products, or the diffusion of rumors, for example. It might be assumed, therefore, that such a modeling approach would be apt for the task at hand. A number of caveats appear, however, upon some reflection.

First, the infected-healthy epidemic model of transmission is unsurprisingly not sufficient to describe social phenomena that may have myriad possible mechanisms, known and unknown. One common development from 'simple' contagion is 'complex' contagion, where the latter is defined as 'transmission [that] requires an individual to have contact with two or more sources of activation' (Centola & Macy, 2007, p.707). Complex contagion has been used in Aral and Nicolaides (2017) for example to model the social contagion of exercise between users of the same running social media app. Complex contagion may not be a coherent where a single interaction may be sufficient for relational diffusion. Moreover, contagion models, and complex contagion models in particular, often assume that multiple instances of exposure after the first should diminish the probability of infection. This runs counter to the mechanism of dialogue discussed here, where it is precisely interactions that form part of the exchange which leads to translated movement application. Indeed, adoption based on neighbors–that

is, where users are followers of each other–is precisely *not* the mechanism of diffusion suggested here. The follower network may affect potential exposure, but the exact details of which users were exposed to which tweet is only accessible by the digital platforms themselves.

Second, the myriad different mechanisms and pathways of spread that are possible there also does not exist a consensus of implementations for contagion models. Aral and Nicolaides (2017) employ an instrumental variable method to complement the complex contagion they model. Iacopini et al. (2019) develop a modeling strategy that incorporates more than pairwise interaction, where the chance of infection for a neighbor receives contribution from both the pairwise connection and the number of neighbors that both nodes of a pair are connected to.

Third, social contagion models, as with the epidemic models of contagion that they draw upon, questions asked of the data often revolve around macro, statistical predictions such as the percentage of total users infected. The only previous work to have utilized social contagion models to model #MeToo takes into account a coefficient of interaction. However, the model only predicts overall volume of tweets, rather than the effect of this interaction on a more micro-scale.

Fourth, yet another hangover from the epidemic inspiration for contagion models is that there is a binary state of being either 'infected' or 'healthy'. Some models include a 'recovered' state, but the same reasoning applies. The concept of movement application requires more than a user to have simply tweeted in a new protest network once. At the very least, there is a qualitative difference between users who tweet once in a new protest network and those who tweet consistently having taken inspiration from the protest network in a different country and/or language.

Fifth, Centola and Macy (2007), Watts and Strogatz (1998), along with much subsequent work, has also assumed that each node–each user–is has equal influence. But it is precisely the thrust of more granular modeling of the interaction between users that there should be a differentiation of level of influence between pairwise interactions such that some pairs have greater influence than others. It is also possible that, for factors external to node interactions entirely, that particular hashtag networks are more susceptible to receiving diffusion on Twitter. For example, Swedish-speaking Twitter users may be more susceptible to diffusion, being a country with greater gender equality than most countries (United Nations Development Programme & United Nations Women, 2023). This is in contrast with a common assumption of threshold models used that assume the probability of infection increases from 0 to 1 once the threshold is crossed, and that the threshold is identical for every node.

Finally, allusions to contagiousness, disease, and epidemics in 'social contagion' presents a potentially unhelpful analogy at least in this context. To suggest that social movement ideas, innovations, tactics, and frames can be understood in this analogy is also to implicitly suggest that these may be 'cured', or that one may 'recover' from them. Whilst this has proven a useful analogy, it is not especially coherent with dialogue.

In summary, social contagion models–though having been previously employed in similar work and also specifically on the #MeToo movement (e.g. Muhlmeyer et al., 2019)–are not applicable for the current task.

3.7.3 Agent-Based Modeling

Agent-based modeling is a method of simulation using agents that enables full control over the world agents inhabit, how the interact, and with what conditions. Agent-based modeling has been used to explain phenomena such as the segregation of neighborhoods without apparent prejudice (Schelling, 1971). They can model complex processes and resulting dynamics with a 'bottom-up' approach, and hence have been used in sociology (Granovetter, 1973) and other disciplines. Agent-based models (henceforth 'ABMs') achieve reduction, scale, and nonlinear dynamics very well. The objective is to identify whether there are regimes under which the dialogical framework of diffusion can occur.

Since ABMs afford such a large degree of freedom, J. C. Jackson et al. (2017) offer seven guiding principles of ABMs that aid its design, which I use here.

1. What are your world's dimensions?

In this instance, the confines of the world are the available #MeToo protest networks that an agent can participate in. Agents are allowed to 'support' a particular network–#yotambien, for example–or not.

2. How do agents meet?

At each time step, agents are able to interact with one other agent. The universe of possible interaction partners for a given agent is the set of agents that they follow on Twitter. Interaction is not guaranteed, and the likelihood of interaction at each time step is a parameter of the model. Every agent is assigned a 'primary protest network' and only interactions between agents of different 'primary' networks are allowed to interact, restricting the model only to transnational–or at least trans-network–dialogical interaction.

3. How do agents behave?

To approximate the theorized phenomena of *translation*, agents can be drawn to support another protest network after a number of reciprocal interactions. To model *experimentation*, agents are able to periodically successfully experiment in a protest network they previously support, which subsequently guarantees that the agent

support that protest network.

4. What is the payoff?

No payoff in the traditional ABM sense is included: agents do not directly 'gain' any advantage over others (money, prestige, resources) in this simulation.

5. How do agents change?

Agents only change insofar as their support for new protest networks grows. Once they acquire support for a new network, they are able to influence others as well.

6. How long does your world last?

The world lasts up to the duration of the sampled periods described in section 3.6.

7. What do you want to learn from your world?

The objective with the ABMs is to examine whether–and if so, how far–a purely dialogical framework is able to reproduce the movement application of #MeToo across different protest networks through the communication channel that is Twitter.

The ABMs had agents with the following properties. First, each agent is considered to have a 'primary hashtag'. This is assigned on the basis of their participation in protest networks *before* the given period to be modeled: the community they tweeted the most in is considered their 'primary' one. Second, agents express support/-participate in protest networks, and their strength of support is represented by an integer. Support is increased through interactions with other agents. Third, at the beginning of the model, a subset of agents are set to be 'supporting' a particular hashtag. A minimum participation before the peak of their primary hashtag is required for agents to be set to be 'supporting' their primary hashtag. Fourth, a time step is taken to be a day. Each time step, agents are allowed to interact with one other agent, sampled from the set of users whom they follow, approximating the exposure to their tweets. Interaction is not enforced: the likelihood of interaction at each time step with any given sampled other agent is a parameter as well. A simple robustness check is whether interactions do occur regularly in the data. Figure 3.4 shows that the number of interactions is variable but not sporadic, and clustered into any particular part of the sampled time period.

To model translation, two mechanisms are built into the agent-based model. In order for the support for a hashtag to be increased: (1) a requirement of reciprocity and (2) a requirement of a minimum number of interactions. Experimentation is modeled by its own parameter: at each time step after having at least satisfied the requirements of the previous step of translation, an agent has a nonzero probability of enacting successful 'ex-

perimentation', understood as encompassing any form that could take, be it with greater likes, retweets, replies, or quotes than usual, or something else entirely. Movement Application is modeled by the strength of support each user possesses, as well as whether a user passes on what they have received from one protest network onto a different protest network that is not their own.

The resulting set of parameters adjustable across the ABMs implemented were:

1. **Interaction Threshold**: The threshold for the minimum number of interactions required between two agents for the receiver to increase support for a particular protest network
2. **Activity Threshold**: The minimum threshold of activity in a protest network at the beginning of each sampled period required for an agent to be considered an initial 'supporter' of that protest network.
3. **Delta**: The number of days before the the peak of the protest network to demarcate the 'beginning' of the agent-based modeling period.
4. **Model number**: Identifiers for the different models that were run, with descriptions below.
5. **Interaction Probability**: the probability of interaction between two agents. At any given time step, an agent may interact with another agent whom they follow on Twitter. This interaction is not guaranteed and the probability it occurs is governed by this parameter.
6. **Interaction Probability Multiplier**: If two agents have interacted before, the likelihood they interact in the next time step is increased multiplicatively by this parameter.
7. **Experimentation Chance**: The probability of experimentation success at any given time step. This parameter only influences the model for agents who have interacted at least once before. If agents have interacted at least once, and the agent in question 'successfully experiments', their support for the protest network for the primary network of the other agent is increased regardless of whether the reciprocal or minimum thresholds of interaction are met.

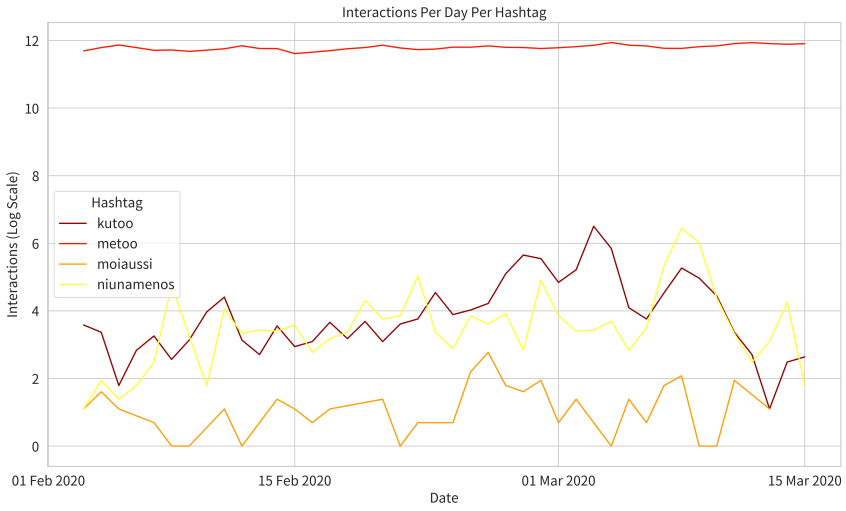
Six models in increasing complexity were as follows, with each model inheriting everything from the model immediately previous unless otherwise specified:

Model 1 has the simplest structure, without differentiation in support across various hashtags. In this model, each user is configured to either 'support #MeToo' or not. There is no room for experimentation, and the only condition for diffusion to happen is the presence of different 'primary' hashtags between two users, given a minimum number of interactions between the two agents.

Model 2 builds on this, necessitating that the agents possess different primary networks for support to escalate.

Figure 3.4

Interactions Across Period 3



Note. This figure shows the interactions between users in the dataset across period 3, demonstrating that the levels of interactions is consistent across the time period, validating the same mechanism in the models.

Model 3 extends the complexity, stipulating a minimum number of reciprocal interactions for support to increase. Models 1, 2, and 3 served as initial checks of the ABM process, and their results are not included in section 3.8.

Model 4 introduces the capacity for differentiated support across multiple networks. For instance, agents may now simultaneously endorse English #MeToo and Catalan #jotambe.

In Model 5, an additional element of experimentation success is integrated into each time step, enriching the dynamics of support diffusion.

Model 6 is the most complex model. Agents are no longer exclusively influencing agents from different primary networks. Additionally, agents can also affect users within their own primary network to support any other network they have been swayed to endorse. For instance, if Agent 1, primarily part of #niunamenos, has been influenced to support #nårdansenstopper by Agent 2, there's a possibility that, in the following time steps, Agent 1 could influence Agent 3 (also primarily of #niunamenos) to support #nårdansenstopper.

3.7.3.1 Evaluating Agent-Based Models

There is no single way to evaluate agent-based models. Some have used a 'distance-to-data' approach (e.g. Carrignon et al., 2020): the difference between the empirical data values and the simulated ones. As an intuitive and interpretable metric, the best performing results on distance-to-data are included in the results. However, it is

important to note that a key aim of the ABM setup in this study is to ask whether a dialogical framework can be used to reproduce and therefore explain the diffusion that is known to have occurred. To that end, additional metrics were developed, split into two categories. These tests and metrics are instrumental in understanding the outputs as they evaluate how well the design of ABMs, and the design of the parameters corresponding to theoretical constructs, can approximate different conceptually important aspects of the observed data.

The first category of tests tackle whether models have adequately captured aspects of the theory they were designed to do:

1. Awareness: whether agents do indeed interact with each other and how many agents interact with other agents of different primary networks.

2. Experimentation: how often agents did increase support for other protest networks through the experimentation mechanism and not through the translation mechanisms.

3. Movement Application: in some sense, movement application is simply the amount of support an agent shows for a particular network. However, for model 6 in particular another test can be conducted: how much secondary diffusion occurred? That is, did agents spread support for a network other than their own primary one?

In some sense, translation is the very core of agent-based models: the interaction between agents. No separate test was devised for translation.

The second category of tests concerns the final output of the agent-based models and how they compare to the known activity data. These are examined in addition to the a distance-to-data metric.

1. Aggregating the agents' support for protest networks at the end of the modeling, is the top protest network #MeToo?

2. As is seen in Figure 3.2, #MeToo is by far the most active protest network in all sampled periods. Is this relative network size present in the results of the ABMs?

3. Relative ranking: is the order of network sizes in data reproduced in the ABMs? That is, are the ABMs able to reproduce how much each network is influenced and grows?

4. Influence network: is the simulated influence between protest networks comparable to that of the observed data?

3.8 Results

3.8.1 Statistical Models

3.8.1.1 RQ1

No statistically significant results were obtained with the aggregate approach. This was clear upon examination of the data, where little correlation or covariance between the independent variables nor between the independent and dependent variables was present. In particular, the activity after the peak of each protest network is surprisingly very low for all three time periods sampled. Full regression outputs are provided in Appendix A.

The modeling yielded no improvements: a forward and backward step-wise search utilizing the Akaike Information Criterion (AIC) was used to determine the best combination of variables for the regression. Often for all three response variables both forward and backward step-wise searches returned the same model with no statistically significant results. In summary, the null statistical results indicate that on aggregate across participants in the protest networks dialogue between users did not result in transnational diffusion. Essentially, this means that the average effect of dialogue on user diffusion was null. Much more interesting however, is the analysis the subsequent agent-based modeling allowed.

3.8.2 Agent-based models

3.8.2.1 RQ1

The agent-based models were found to be able to faithfully reproduce empirical data across metrics for all the evaluative metrics. This demonstrates that they were able to faithfully capture dialogical diffusion.

The parameters and the respective values taken in the modeling were as follows in Table 3.2, in the same order as described in above. To account for the probabilistic nature of the agent-based model setup, each parameter combination was run 20 times, for a total of 129,600 runs.

The percentage of agents who were assigned each protest network across all runs is displayed in Table 3.3.

The first category of evaluation measures were intended to ensure that the ABMs did indeed capture each aspect of the dialogical framework. Beginning with awareness–the number of successful interactions between users of different primary support networks–the ABMs showed that the random sampling of users to interact with from their follows was sufficient to generate enough interactions to initiate the process of dialogical diffusion. The distribution of awareness counts across models in each period is displayed in Figure 3.5. The levels of awareness were predominantly controlled by the interaction probability parameter, allowing the ABMs to empirically

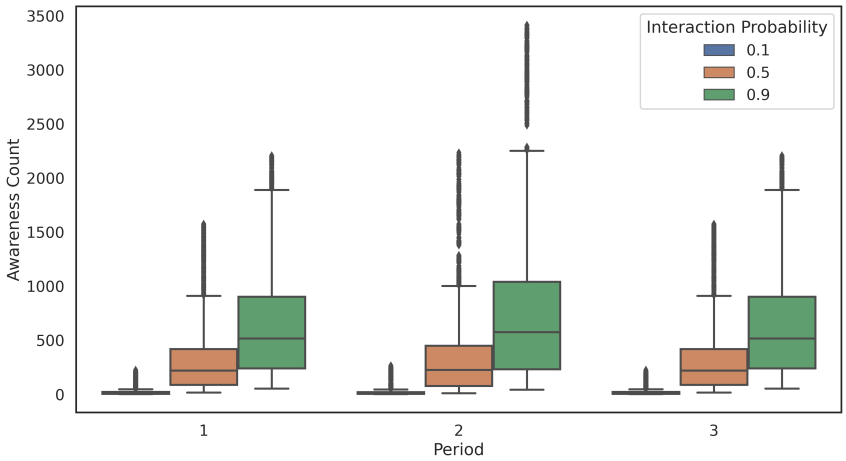
Table 3.2

Parameter Combination Ranges

Parameter	Range
Interaction Threshold	1, 2, 3, 4
Initial Activity Threshold	1, 2, 3
Delta	3, 5, 7
Model Number	4, 5, 6
Interaction Probability	0.1, 0.5, 0.9
Interaction Probability Multiplier	0.9, 1.0, 1.1, 1.2
Experimentation Chance	0.01, 0.05, 0.1, 0.2, 0.3

Figure 3.5

Awareness Counts in Agent-Based Simulations



Note. This figure shows a boxplot of awareness counts for each of the sampled periods grouped by interaction probability. Awareness is counted as the number of times interactions were successful between users of different primary protest networks.

determine, on this design of agents' interactions, the parameter value required to reproduce observed data.

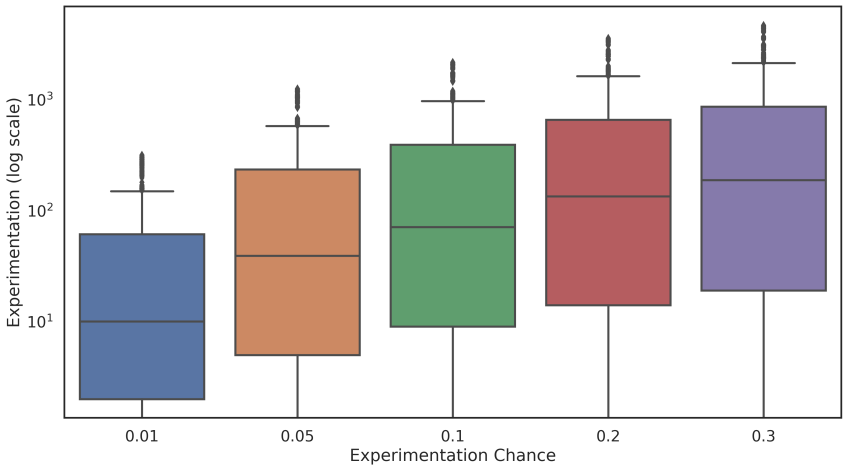
Notably, even when the interaction probability is set high at 0.9, the awareness count for any sampled period reaches only up to 2% of the total interactions between agents. This property bolsters the validity of the ABM design, as it is consistent with Chabot's assertion that the dialogical process of diffusion is rare.

Next, experimentation occurred in all sampled periods in the majority of parameter sets, and was most influenced as expected by the experimentation chance parameter. This is shown for Period 3 in Figure 3.6. This verifies the ABMs ability to account for influencing protest network support between agents *not* through the regular translation mechanism.

Figure 3.7 shows the distribution of secondary diffusion, where one agent A influences another agent B to

Figure 3.6

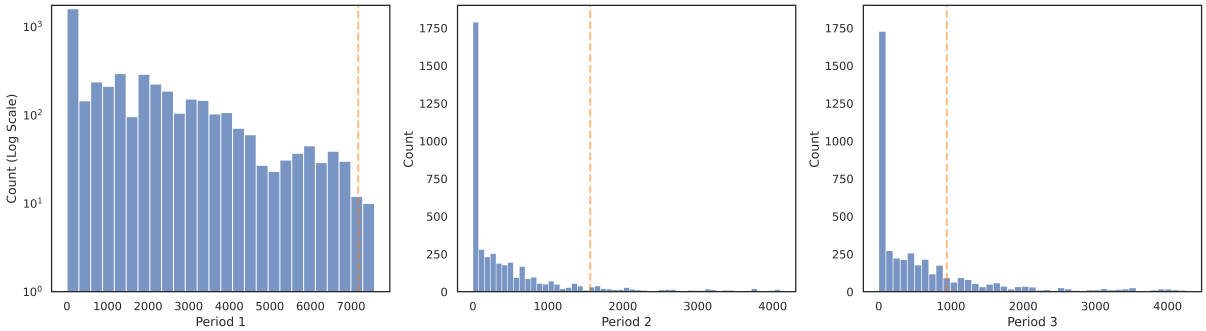
Experimentation Counts Against Experimentation Chance for Period 3.



Note. This figure shows the experimentation counts for resultant models in period 3, against the 'Experimentation Chance' parameter. The bottom of each whisker of the boxplots descends to 0 as no experimentation occurs in models with no awareness.

Figure 3.7

Distributions of Movement Application due to Secondary Diffusion in Model 6



Note. This figure shows the movement application counts in Model 6, in log scale, for each period. Dotted lines indicate actual total movement applications per period. Model 6 allows for secondary diffusion, where one agent A influences another agent B to support a protest network other that $A's$ original primary one. Only with this secondary diffusion mechanism were models able to reach the empirical levels of movement application observed, illustrating the importance of allowing this mechanism to better approximate actual processes.

Table 3.3

Distribution of Agents across Primary Protest Networks

Protest Network	Percentage		
	Period 1	Period 2	Period 3
metoo	82.88	62.54	63.20
timesup	7.17	1.31	1.04
niunamenos	4.65	17.39	16.91
cuentalo	3.82	1.83	3.02
kutoo	0.52	5.36	0.60
wetoo	0.40	0.55	0.27
balancetonporc	0.21	3.17	5.08
withyou	0.21	0.85	0.82
noustoutes	0.07	4.06	6.74
moiaussi	0.02	1.12	0.97
quellavoltache	0.02	0.23	0.48
yotambien	-	1.01	0.61
enazeda	-	0.29	0.01
jotambe	-	0.14	0.08
sendeanlat	-	0.09	0.09
niere	-	0.03	0.04
ricebunny	-	0.01	0.02
watashimo	-	0.01	-
woyeshi	-	-	0.02

Note. 'Primary' indicates the starting protest network an agent initially belongs to in the agent-based models.

support a protest network other that $A's$ primary one, across the three periods. The dotted lines indicating the total movement application for each period, showing that the ABMs were able to account for a substantial proportion of diffusion and therefore was an important mechanism to include. Therefore, the ABMs have shown that they possess the required modeling capabilities, each capability correctly corresponding to the aspect of dialogue as required.

The second category of evaluation measures related to the data outputs of the ABMs. The best distance-to-data results are displayed in Figure 3.4, Figure 3.5 and Figure 3.6. For all periods, ABMs simulated support levels for most networks remarkably close to their actual values. This is most pronounced in periods 2 and 3. Not only have the ABMs demonstrated their ability to adequately capture theoretical working through the first category of evaluative tests above, they demonstrate that they can achieve a high proximity to observed data.

As is seen in the observed data, English #MeToo is always the largest protest network in each of the sampled periods. All ABMs models in every parameter configuration were able to reproduce this behavior. This indicates that the ABMs were able to correctly identify the English network as the original and most populous.

Table 3.4

Distance-to-Data for Period 1

Network	ABM	Actual
metoo	3985	3346
timesup	2094	3038
niunamenos	225	250
cuentalo	55	205
wetoo	434	113
withyou	258	100
balancetonporc	72	61
私も	2	31
moiaussi	15	11
memyös	8	8
quellavoltache	22	6
ricebunny	4	2
stilleforopptak	0	2
woyeshi	0	2
yotambien	12	2
ятоже	1	1

Note. This table shows the ABM result with minimum distance, calculated by simple subtraction, to empirical results for period 1.

The data also exhibited the property of the English #MeToo networks being far larger than any other present protest networks in a sampled period. Is similar behavior exhibited in the simulated output? Figure 3.8 shows the distribution of the percentage difference between the English #MeToo network and the second largest network in the simulated data, where the red line for each sampled period indicates the empirical reference value. Figure 3.8 shows that the simulated ABM gap is typically larger in size than the empirical gap. The ABM setup typically overestimated the amount of support for the English #MeToo networks. However, the best performing parameter combinations were able to approach the true percentage difference, as shown by the proximity of the lowest part of the boxplots for each period to the red lines.

Lastly, Congruence of rankings of protest network size between empirical and ABM data would further strengthen the results. Omitting the English #MeToo as it was the largest network, Spearman's rank correlation coefficient was calculated for the protest networks second to fifth in size for all the parameters sets. Spearman's rank correlation coefficient is a measure of how well two ranking lists match. It can take values between -1 and 1, where the former means the rankings are inverses of each other, and the latter means the rankings are identical. For example, the lists (first, second, third) and (third, second, first) would have a Spearman's rank correlation coefficient value of -1. Figure 3.9 and Figure 3.10 show the distribution of these correlations between the simulated and observed rankings of protest network size in period 1 and period 2 respectively. If the coefficients are able

Table 3.5

Distance-to-Data for Period 2

Network	ABM	Actual
metoo	752	752
noustoutes	145	530
niunamenos	269	266
moiaussi	18	11
wetoo	14	7
ятоже	0	0
米兔	0	0

Note. This table shows the ABM result with minimum distance, calculated by simple subtraction, to empirical results for period 2.

Table 3.6

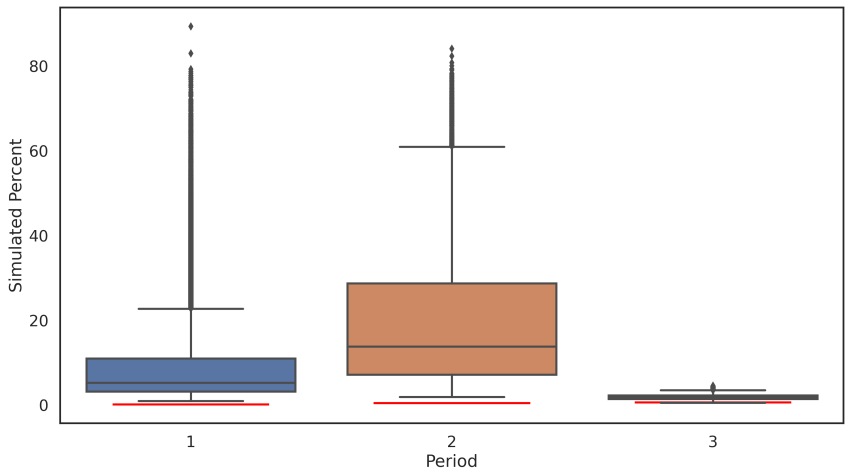
Distance-to-Data for Period 3

Network	ABM	Actual
metoo	474	472
kutoo	261	295
niunamenos	161	163
moiaussi	11	13

Note. This table shows the ABM result with minimum distance, calculated by simple subtraction, to empirical results for period 3.

Figure 3.8

Size Differences Between Simulated English #MeToo and Second-largest Networks

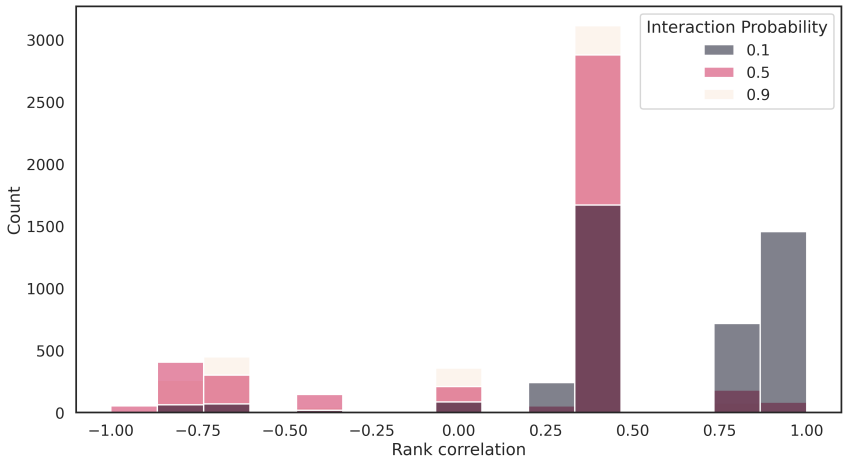


Note. This figure shows the distribution of percentage difference between the size of English #MeToo and second largest protest network in the agent-based modeling results. Red lines indicate the actual percentage difference. If agent-based models are to faithfully reproduce empirical results, they should reflect the fact that English #MeToo networks are significantly larger than the second largest networks. A correspondence between the empirical and simulated differences illustrates the capability of agent-based models to capture empirical patterns.

to achieve perfect (1) or high correlation, then we have demonstrated that the ABMs can reproduce this aspect of the empirical data behaviour. Figure 3.9 and Figure 3.10 also show that interaction probability had a significant impact on this metric, though with notable variation between the period. For period 1, a lower interaction probability resulted in higher rank correlation, where the opposite was true for period 2. This strengthens the case that ABMs are able to reproduce this behavior as its flexibility for different parameter scenarios allows for a robustness in capturing actual patterns. Other parameters had less noticeable effect on the the rank correlation.

Figure 3.9

Rank Correlations Between Simulated and Actual Data for Period 1



Note. This figure shows a stacked bar plot of rank correlation between empirical and ABM data for second to fifth protest networks in period 1, colored by the interaction probability. A higher rank correlation indicates greater agreement in the relative rankings of simulated and empirical data, and the more often this occurs in the simulated data the more capable the ABMs are.

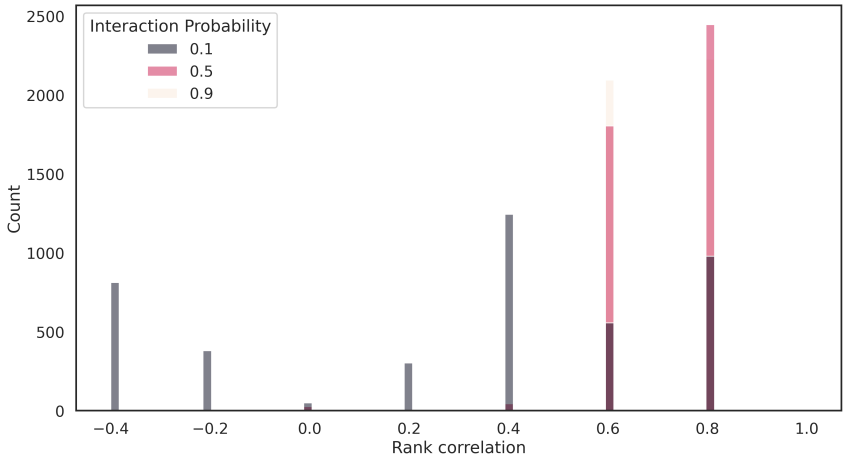
In summary, agent-based modelings was able to reproduce multiple features of diffusive behavior in separate time windows. That this was possible suggests a robustness to the operationalization of dialogue presented, and the heterogeneity of the parameter combinations required also indicates not only that an ABM approach can capture a range of difference diffusive scenarios and outcomes, but also that the way dialogue contributes and enables diffusion might occur in a variety of ways.

3.8.2.2 RQ2

Which networks have been received and transmitted more is something both observable in the empirical data and that can be simulated in the ABMs. Figure 3.11 displays the empirical influence graph between influence networks in period 2, where each node represents a protest network and directed edges between nodes indicates the presence of influence from participants from the source protest network to the target. The size of each node is directly proportional to its outward influence, i.e. its influence on other networks. Unsurprisingly, English

Figure 3.10

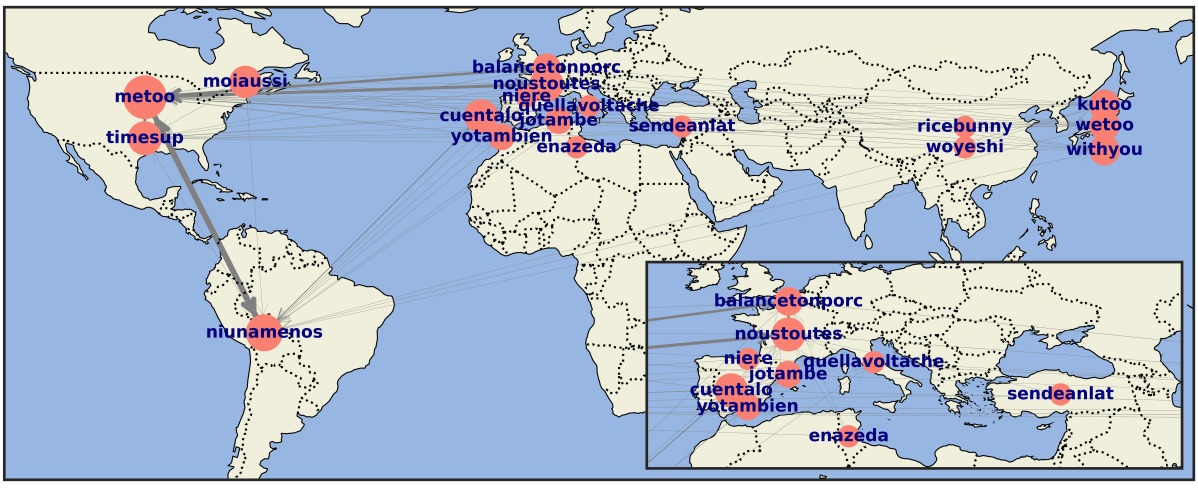
Rank Correlations Between Simulated and Actual Data for Period 2



Note. This figure shows a stacked bar plot of rank correlation between empirical and ABM data for second to fifth protest networks in period 2, colored by the interaction probability. A higher rank correlation indicates greater agreement in the relative rankings of simulated and empirical data, and the more often this occurs in the simulated data the more capable the ABMs are.

Figure 3.11

Network of Interactions Between Protest Networks



Note. This figure shows a directed network visualization of protest networks and interactions between constituent users across languages for period 2. Nodes are protest networks and edges are interactions between users of those languages. Edge width is proportional to the volume of interaction between the protest networks. Nodes are overlaid onto a world map with known associated countries. An inset figure in the bottom left shows an enlarged European and North African region in bottom right for visual clarity.

#MeToo is still the most influential node. Notably, however, only #ricebunny exhibits connections to #MeToo solely: every other node has influence with other nodes. Quantitatively, graph density for Figure 3.11 is 0.405. Its height was 11, and structural virality was $\nu(T) = 10.28$. Recalling that structural virality is maximized for structures that are large and have become that way through many small branching events (i.e. where language networks have influenced each other), both density and structural virality show that the perhaps contrary to how the #MeToo movement has been conceived of in scholarly and news media reporting, it truly was and is an international phenomenon that has horizons much further than the English-speaking world.

3.9 Discussion and Conclusion

This study considered two approaches to the first research question **RQ1** on the effect of dialogue on movement application. First, a statistical approach sought to examine if signals of dialogue's effect were apparent at a time-aggregate level. That returned a null result, suggesting dialogue did not affect the transnational diffusion of #MeToo, providing evidence for hypothesis **H1a**. This was true across all three sampled time periods, both on aggregate and upon closer inspection of the effect of on individual protest networks. Even when an user who was individual and not an organization interacted many times and had successful experimentation in their tweets in a different language, this direct contact very rarely resulted in noticeable relational diffusion.

Critically, however, the second approach of agent-based modeling approach showed that even with a few parameters specifically designed to operationalize Chabot's dialogical framework, diffusive behavior was reproducible under a number of evaluation metrics over three sampled periods spanning three years. This both suggests relational diffusion does indeed occur between a large number of languages and communities through Twitter, and lends support to the dialogical framework of transnational diffusion. This not only provided support for hypothesis **H1b**, but further allows the conclusion in answer to **RQ1** that by virtue of the robustly reproduced diffusive effects driven by dialogue in the agent-based modeling, dialogue *does* indeed substantially explain the transnational diffusion of #MeToo on Twitter. Relational diffusion can explain a substantial amount of diffusion on digital platforms, in contrast to non-relational (not interpersonal, for example through news reports) and mediated diffusion (brokered connections).

For **RQ2**, diffusive effects were found to occur between many different communities, in contrast with more uni-directional, broadcast type diffusive effect from the original English #MeToo to others. This was consistent with hypothesis **H2**.

In answering the research questions, this study contributes methodologically. Agent-based models were chosen because of their flexibility in design, but required numerous non-trivial choices to be incorporated into the

design: how can 'awareness', 'translation', 'experimentation', and 'movement application' be adequately captured in the mechanism of the agent-based models, and how well can the mechanisms correspond to the structure imposed by Twitter? This study devised explicit measures and mechanisms corresponding to each one: for example, that translation should be modeled through repeated interaction not including simple retweets, each moving an agent towards supporting another protest network. Additionally, a suite of evaluative measures were devised and imposed upon the models, providing robustness to the results. These methodological contributions show how theoretical frameworks can be applied to and tested in social media and digital platforms more broadly, thereby expanding the theory.

A number of noteworthy considerations and caveats should be mentioned. First, It is still possible that relational, dialogue-driven diffusion occurs on Twitter, but predominantly through direct messages, for example. Direct messages is a documented method of building and sustaining connections between activists in a social movement context (Penney & Dadas, 2014).

Second, the role Twitter plays in different political contexts is not uniform. For example, Twitter is not accessible from within China, and some hashtags in Chinese such as # 米兔 would not refer to any community *within* the country per se, but rather to a wider Chinese diaspora.

Third, the seed list of hashtags here, though are known and are mostly derivative or grounded in '#MeToo', are not exclusively so. For example #NiUnaMenos has been used in South America for movements against femicide.

Fourth, some of the empirical results and simulated ABM support for protest networks is zero even peaks exist for those protest networks. This was due to the sampling of users in each time period: users were sampled from each protest network, but their 'primary' networks were not necessarily those for which they had been sampled.

Fifth, one unavoidable limitation of the data collection is that the follower network cannot be collected retrospectively through the Twitter API. It is impossible to know, therefore, whether the follow relations between users who interacted in the agent-based models were already existent at the time of time sampling periods, or was formed after–and potentially because of–the interactions between them.

Finally, as mentioned in the data collection and cleaning process, bots were not excluded for several reasons. The effective cleaning of bot would have taken far more resources than available for a dataset of this size, but may be of interest for future studies of a similar design.

We hope that the theoretical and methodological contributions of this work can spur similar analyses of social movements in computational social science.

3.10 Future Work

Some limitations of this study have already been discussed, and lend themselves well to suggestions for future work. Whereas this study contributes a number of operationalizations and applications of diffusion theory, different measures of dialogue and diffusion may be developed to further this area of social movement research. First, this study also opens up future work on valuable qualitative studies that can dig deeper into the nature of dialogue and diffusion on Twitter, and inform therefore how future quantitative studies can contribute to its study. Fruitful future work might include, for example, a fuller qualitative analysis into the the dialogical mechanisms of diffusion at play on Twitter and other digital platforms. Given the that there is no fixed way to operationalize the concepts discussed, a qualitative analysis of such data might yield new concepts that allow for a revision of diffusion theory. Second, the agent-based modeling approach described is easily extendable to other movements. Third, there is much unexplored ground in both the setup of similar agent-based models and how they can be evaluated in the context of social movement theory.

Chapter 4

Article II: The Effect of #MeToo on Rape Myths in the Media: A Global Multilingual Analysis[1]

4.1 Introduction

The #MeToo movement has been a strongly influential movement in more than 85 countries (A. Park, 2017): for example, it has helped survivors reclaim agency and stigmatized narratives about sexual violence (Boyle, 2019a; Gallagher et al., 2019) , increased reporting of historically under-reported sexual crimes in 30 OECD countries (Levy & Mattsson, 2020; Thompson & Tapp, 2022), and generated momentum for greater gender equality through legislation (Song, 2023). Although initially sparked on Twitter, media outlets and platforms that allowed #MeToo to become the movement were just as central as individual testimonies on social networks (Boyle, 2019a). Social media enabled an unprecedented ability to directly participate in connective action: action that is characterised by communications platforms subsuming traditional social movement organizations and constituting organizations in their own right in social movements, giving rise to more loosely structured and more personalized forms of engagement (Bennett & Segerberg, 2013; Zeng, 2020). Twitter, however, represents a small subsection of the population of any country, and the audience it reaches is therefore limited (Blank & Lutz, 2017). News media not only by contrast have a wider audience and reach, but are also a major site of contention between social movements and political authorities (Koopmans, 2004; Zuckerman et al., 2019). How news media responded to the movement, therefore, is of interest. Indeed, the dynamics between social movements and their coverage by news media is a rich body of research (McCurdy, 2012).

One of the core aspects of the movement was its call to attention on how widespread and endemic sexual harassment and assault are around the world. For feminist movements in particular, scholars have found of nu-

[1] N.B. This article was co-authored with Joana Perrone. Please find a statement of of contribution in Appendix C.

merous in which mass media tend to—intentionally or otherwise—undermine, misrepresent, render invisible or depoliticize women's movements (Ashley & Olson, 1998; Bronstein, 2005; J. Lee, 2020). How media outlets take into account this call to attention in their coverage within the existing tendencies of what is also known as the 'protest paradigm' (Chan & Lee, 1984; Harlow et al., 2017), for a global movement, is the subject of our investigation. More specifically, these diminishing practices well documented by scholars often appear as rape myths.

Rape myths are generalized and false beliefs about sexual assault that trivialize a sexual assault or suggest that a sexual assault did not occur (Franiuk, Seefelt, & Vandello, 2008). More emphatically, rape myths are not only harmful in their falsity but do significant damage because they can and are employed to downplay or dismiss sexual assault, harassment, or violence. They solidify patriarchal ideas and the idea of a 'just world' that dictates good things happen to good people and bad things happen to bad people (Lerner 1980). Widespread acceptance of rape myths is a perennial problem, and their appearance in news media serve to reinforce the public acceptance for them, which consequently not only shapes the very definition of sexual violence (Heberle & Grace, 2009), but acceptance of rape myths has an impact on an individual's likelihood of committing sexual assault (Bohner et al., 2005; Lanier, 2001).

Much of the research on the rape myths present in media reports has hitherto been qualitative through content, thematic, or discourse analyses of news text (Askanius & Hartley, 2019; O'Hara, 2012; Silveirinha et al., 2020), both for the #MeToo movement and otherwise. However, in order to understand how what the impact of #MeToo is internationally, different methodologies are required to match its multicultural reach and the volume of digital traces produced (Stubbs-Richardson et al., 2023). Drawing from the typologies of rape myths from these previous works, this study employed a novel mixed methods analysis to understand the impact #MeToo had on rape myths in the media, employing an annotation of a sample of news media in Chinese, English, and Spanish, the fine-tuning of a language-agnostic BERT model LaBSE (Feng et al., 2022). The central research question posed was: what was the impact of #MeToo on the presence and frequency of rape myths in news media around the world? This research question is broken down into a number of sub-questions. First, to address the longevity of any observed changes: did countries in which #MeToo have an impact maintain those changes?

Clearly, there are important differences between the sexual ethics, gender norms, and institutionalized attitudes towards sexual assault (Flaskerud, 2019). These form part of the 'political openness' of a country to the campaigns of social movements, a factor theorized to affect the outcomes of those social movements (Dalton et al., 2010; Meyer & Whittier, 1994). This motivates the second sub-question: How does political openness affect

whether or not there is an impact, if at all?

Finally, there may be variation in how rape myths are employed in the coverage between different people accused of sexual assault. Scholars have noted how, for example, a protest's geographic proximity to the newsroom has affected coverage of the protest (Koopmans, 2004). This motivates the final sub-question: How does geographic proximity of the subject affect the presence and frequency rape myths?

This study contributes both in expanding research on the outcomes of modern digital activism, but also in the methodologies employed in social movement research: we (1) formulate a table of rape myths synthesizing existing work from feminist literature specifically for application with computational social sciences, (2) use these rape myths to annotate articles in Chinese, English, and Spanish and propagate labels throughout the dataset using language-agnostic embeddings, (3) apply a Bayesian Structural Time Series to determine the impact of #MeToo on media uses of rape myths controlling for background factors, and (4) present a methodology on the basis of rape myths for contrasting media representations across geographies.

With these contributions, we find that though the prevalence of rape myths diminished in a minority of countries the year after #MeToo took hold in those respective countries, these effects often did not last. Moreover, the differences between political, social, and cultural contexts between countries did *not* explain which countries' media were more or less likely to alter their representations of sexual violence in this respect. We contend this means **rape myths are extremely deeply institutionally ingrained in the public consciousness and resistant to change**, regardless of geography.

4.2 Related Work

4.2.1 Social Movements and the Media

Social movements and news media have had a longstanding history, and scholarship on the relationship between the two have long been of interest (McCurdy, 2012).

The development and ultimate impact of a social movements and their media representations are linked. The interpretive packages media institutions offer can either impede or promote activism (Gamson & Modigliani, 1989, p.2). Scholars have noted before, for example, how media coverage of protest events can alter how they come to be policed (Della Porta & Fillieule, 2004). In general, research has pointed to activists needing media coverage to help spread the messages of contentious politics, but have found that in order to garner such attention more radical tactics need to be employed (Gitlin, 1980). Such tactics are likelier to generate negative attention, a media practice understood as the 'protest paradigm' (Chan & Lee, 1984). Stories within the paradigm

are characterised by favoring the status quo and the de-legitimization of movement advocates (McLeod & Hertog, 1992). Whilst the universality of the protest paradigm is disputed (Harlow et al., 2020; Shahin et al., 2016), scholars agree that it is widely applicable. Already we expect a bias against survivors and activists of #MeToo, consistent with the analyses of feminist scholarship discussed below.

Communications research has shown a number of selection criteria that influence coverage and interpretive packages employed by media (Gamson & Modigliani, 1989; McCurdy, 2012). In particular, the size of the protest event, the protest's geographic proximity to the newsroom, the level of conflict, and the prominence or prestige of the speaker or target (Harlow et al., 2020; Koopmans, 2004). Naturally, these criteria are known to social movements organizations and organizers. Modern protests, feminist or otherwise, have tried to stage and design protests so as to maximize chances of media attention (Henn & Posegga, 2023). However, there are substantial limits to the visibility that can be directly controlled by organizers, as evidenced by the 'abstention' that some social movements have employed: a withdrawal from the attempts to influence the media (Rucht, 2004).

How these selection criteria apply to digital activism, however, is unclear. One defining feature of digital activism, and *connective action*, is that they are not structured in the same way as traditional social movements that had organizing institutions and clear leadership (Bennett & Segerberg, 2013; Zeng, 2020). How does size of protest apply for #MeToo? Though there have been prominent public demonstrations, much of the movement was characterised by its digital presence. Level of conflict and prominence of speaker can also be difficult to quantify. Geographic proximity, however, been media outlets and instances of sexual assault allegations in the media may be observed even for digital activism, and will be examined in this study.

Beyond the individual properties of events and specific media outlets, much social movement scholarship has found that what is called 'political opportunity structures' play an important role in how social movements mobilize (Tilly & Tarrow, 2015). The concept of political opportunity refers to the mobilization of resources that are *external* to an activist group. These may be configurations of resources, institutional arrangements, historical precedents and cultural factors that enable or hinder the development of social movements (Kitschelt, 1986). When these resources are available and are accessed, challenges to elites–those holding onto and benefiting from the status quo–may be challenged. Then, when the capacity of a state to repress challenges to elites declines, or when the perceived injustice is so great as to overcome or ignore a state's capacity for repression, cycles of mobilization and social movements occur. That is, the political regimes and socio-cultural particularities of a country guide the possible and actual contours of contentious politics.

Though not deterministic, and often non-linear and complex in its effect (Dalton et al., 2010), political open-

ness is theorized to be able to explain a good deal of the variation between the courses of social movements in countries with more political opportunity, or higher political openness, and those with less political opportunity, or lower political openness. A more authoritarian regime is likelier to employ physical repression, thereby necessitating the level of violence in repertoire of protest tactics employed (Meyer, 2004). A highly centralized media ecosystem might lead challengers to seek alternate routes of (self-)publication and dissemination in an authoritarian regime, in contrast with 'high-capacity democratic' regimes (Tarrow, 2022) where the greater rights of citizens enable continual contention, and the decentralization of power lowers the risk of conventional contention escalating into revolutionary contention.

With regards to feminist movements, the same logics apply. Scholars have argued that the presence of a more direct democracy can indicate a greater openness to women's voices and therefore encourages political participation (Kim, 2019). In a closed political system, conversely, those outside the ruling or dominant political group may not feel that their chances of making political gains are significant, and therefore are less likely to participate. In terms of the the media and political opportunity, Gamson and Meyer (1996) indicate higher political openness being linked to the easing up of the media space.

More specifically, some dimensions of opportunity are repression, increasing access, shifting alignments, divided elites, and influential allies (Tarrow, 2022, p.145). In relation to feminist movements, repression encompasses women's rights such as abortion rights, the access to justice, the freedom of discussion for women, etc. in addition to the control of media: whether media is centralized and/or censored. Increasing access might mean greater access to institutional power, or more women in offices of political or otherwise elite status. Shifting alignments and divided elites might encompass visible conflict between politicians and public figures about gender equality and women's rights, and in this case how they individually and society more broadly should respond to the ubiquity of sexual harassment and violence. The presence of influential allies, such as more women as lawyers and judges in courtrooms, may enable more challengers against the status quo. As will be discussed further below, the Varieties of Democracy indices is a rigorously produced set of measures that relates to these dimensions of opportunity, and therefore an apt operationalization of political openness across the countries included in this article.

All of the foregoing factors ultimately contribute to forms of media representation, which is formalized as framing. Predicated on the idea that the media both reflects and actively shapes public discourse and understanding, media framing is a key mechanism through which scholars believe social movements and media to be linked. Media framing is believed to be able to affect the public's understanding of events and movements more broadly through the emphasis of certain elements in a news story over others (Gitlin, 1980). Gamson and Modigliani

(1989) conceptualized frames as the core representation of reality present in a news article. In more modern analyses of media framing. Entman's 1993 definition of a frame has been very commonly employed. Entman (1993) refined Gitlin's (1980) definition so as to claim a frame to be '[selecting] some aspects of perceived reality and make them more salient in a communicating text, in such a way as to promote a particular definition of a problem, causal interpretation, moral evaluation, and/or treatment recommendation for the item described' (Entman, 1993, p.52). It is this understanding of framing that the scholarship discussed in the rest of this section uses. In particular, rape myths are understood in this study as frames employed in the media. The heavily interpretive and morally evaluative nature of rape myths is evident.

4.2.2 Feminist Scholarship on Media

Feminist scholars have also taken a keen interest in the role of the media. Like social movement scholars, feminist scholars have also argued that discourse on feminism has only been in partial control of feminist activists. News media has often perpetuated and hence reinforced established understandings of sexual assault and violence (Dwyer et al., 2012; Franiuk, Seefelt, Cepress, & Vandello, 2008; Palmer-Mehta, 2018). The first mechanism is the choice of coverage. For example, Kitzinger (2004) has detailed how traditional media often focuses on cases meeting a legal threshold of sexual assault or violence. Not only do cases go under-reported by the legal action threshold, the same under-reporting occurs when activists have advocated against violence against women and reform of laws on sexual violence (Moorti, 2002). All the foregoing problems are compounded by the fact that feminist scholars have long argued that the legal system does not serve survivors (Maquin, 2020). Further, other factors such as the race of the accused have been shown to affect the framing and coverage of sexual violence against women (Moorti, 2002), tying into Crenshaw's (1989) concept of intersectionality.

Lexical differences appear in how allegations of sexual violence are presented. In recent scholarship the same tropes and reproductions of rape culture have been found in the last few years of news coverage (Cuklanz, 2020). For example, allegations leveled against women are often presented as gender issues, whereas allegations against men are not. By coding one as 'gender issues' and the other as not, it appears as if women's alleged transgressions are able to inform on 'gender issues' whereas transgressions by men do not. 'Gender' as, is often used interchangeably with 'women', implies that 'gender-based violence' and 'violence against women' are the same (Boyle, 2019b).

Other times, traditional media upholds and reinforces rape myths. Examples include implicit suggestions that survivors are lying, deserved the assault, or that the perpetrator had to be a 'stranger in a dark alley'. Brownmiller (1975) and Burt (1980) were early to identify and discuss rape myths in Western culture, though research clearly

shows rape myths and culture are highly international (Makin & Morczek, 2015). Myths, in general, have three key characteristics: they are false or apocryphal beliefs that are widely subscribed to, they explain some cultural phenomenon, and they serve to justify existing cultural arrangements (Lonsway & Fitzgerald, 1994). Rape myths are no different: their power originates from their ability to solidify patriarchal ideas and institutional practices and the idea of the 'just world' that dictates good things happen to good people and bad things happen to bad people (Lerner, 1980), and to allow men to distant themselves from the 'bad apples' who commit sexual assault.

If rape myths were scarcely used or were promptly discounted when they were used, there would be little cause for alarm when they surfaced. However, rape myths are used widely by both men and women (Lonsway & Fitzgerald, 1994). The level of sympathy and anger against the perpetrator is often proportional to the level that case conforms to the 'vicious attack by a stranger in a dark alley' script. Conversely, survivors are disproportionately disparaged, undermined, and discounted when when the case deviates from the conceptual confines of such a rape myth (Frese et al., 2004). These effects make survivors more vulnerable to sexual assault by invalidating their experiences and continuing to diminish their agency.

Not only do rape myths affect the way people perceive it is also important to assess the impact that endorsing rape myths may have on an individual's propensity to commit sexual assault. Men's endorsement of rape myths is correlated with their admitted likelihood to commit sexual assault if assured no repercussions (Bohner et al., 2005), reinforced by longitudinal research (Lanier, 2001).

These myths appear frequently in news media reporting, including during prime time television (Brinson, 1989). Scholars have argued empirically that rape myths in headlines solidify the public's acceptance of rape myths, typically with greater effect on men than on women (Franiuk, Seefelt, & Vandello, 2008).

As some scholars have argued, there is no fixed definition of sexual violence (Heberle & Grace, 2009). Therefore, traditional media's role in constructing the boundaries of sexual violence through their use of rape myths becomes all the more apparent. News media is especially potent in forging public understandings of sex, consent, and sexual violence (E. K. Johnson, 2017; Waterhouse-Watson, 2016), even if it is one of a number of influences on public opinion. As shall be discussed further in the following section, though some work has emerged on particular examples within #MeToo of media coverage, a wider multi-national examination of such media constructions has not been conducted. Only such a multi-national study would further understanding the influence and legacy of a movement with the reach of #MeToo.

4.2.3 Feminist Scholarship on Media in the #MeToo Context

Research on media representations of sexual assault as pertains to #MeToo have predominantly been small-scale and qualitative: this study seeks to complement previous work by expanding the scope of examination. Typically, studies in this context have centered around a number of high profile cases associated with #MeToo. Hindes and Fileborn (2019), for example, examine media framing around the case of comedian Aziz Ansari as covered in Australian news outlets. A survivor initially known as 'Grace' had leveled accusations against the comedian in a case that was a divisive and high-profile case in the U.S. They apply a post-structuralist account of sexual violence built upon Liz Kelly's widely used concept of a continuum (Kelly, 1987), which foregrounds the broad range of experiences and behaviors that can cause harms, especially those beyond legal boundaries. On such an account the definitions of sexual abuse and violence shift with political, social, and cultural contexts (Heberle & Grace, 2009). Ansari's case was chosen for its prominence as a 'grey area' case where discursive construction would be most revealed. By shifting the focus to the survivor's ('Grace') subjective experience, media had consistently downplayed the incident as non-violent. In so doing, the incident could be construed as an implicitly consensual affair and the subsequent furor simply the bitter vengeance for 'bad sex'. Other outlets still presented pressure and coercion as a part of a patriarchal script of heterosexual encounters (Gunnarsson, 2018). The case of Ansari and Grace merely illustrated how sexual activism had 'gone too far'.

Like Hindes and Fileborn (2019), Cuklanz (2020) examined a small corpus of articles from *The Washington Post* and *The New York Times*. They found similar themes of victim-blaming, concentrating attention on the accused and their potential professional loss in the cases of Matt Lauer and Charlie Rose. Typically, the established influential roles of the two men in question were foregrounded in coverage before substantive outlines or explanations of the accusations in question were given. Boyle (2019a) determined the same for coverage of Harvey Weinstein.

Orgad and Gill (2019) dove deeper into the coverage of Uma Thurman's case. Focusing on the pathologization of female rage, and especially that of women of color (Ahmed, 2010), Orgad and Gill (2019) argue that there were three major cases of Thurman's anger being contained through a 'safety valve' (Berlant, 1988). A 'safety valve' complaint is one that permits self-containment that does not seriously challenge the patriarchy, but that maintains some oppositional nature. Complaints therefore do not challenge the deeper, fundamental conditions which produced the complaint's origin and so these complaints become a 'safety valve' through which female anger may be channeled and controlled. In Thurman's case, this manifested initially when she denied the media a 'tidy sound bite' because she had often regretted the way she expressed herself afterwards. The self-moderation of anger was praised for poise, control, and restraint. Then, just as Berlant describes, coverage of

Thurman subsequently choosing to express this anger focused on the anger *itself* as the story, and not at all on the reasons for her anger. Finally, her anger was re-contextualised and repackaged into a narrative of self-help, where again a narrative was constructed about Thurman's self-realisation and personal growth, deflating and rendering the anger palatable and harmless, erstwhile tacitly ignoring protest against sexual violence.

Some studies have examined coverage in Asian contexts. Lee (2020) examined traditional media coverage of #MeToo in the context of South Korea. They went further in questioning the impact of #MeToo on traditional news coverage by comparing cases before and after #MeToo's rise in South Korea: coverage of the former National Assembly Speaker Park Hee-tae before and the sexual assault case of former National Assembly member Ahn Hee-jung after the #MeToo movement broke out. Both were public figures accused and later convicted of sexual assault. Lee (2020) found that there was little difference before and after the rise of #MeToo in South Korea in the framing South Korean news outlets used. Further, Lee determined that there was no statistical difference in how inequitable the presentations of men and women were in reports of sexual assault cases before and after #MeToo in South Korea. However, Lee additionally found that a significant increase in reports describing and highlighting the viewpoints of survivors after #MeToo. On this basis she concludes that the movement had a strong enough impact attitudes in South Korea that traditional news media outlets adopted new reporting practices, though not enough to substantially change other aspects of coverage towards sexual assault cases.

A few studies considered the cross-national scope of #MeToo. Askanius and Hartley (2019) compared news framing of #MeToo stories across Denmark and Sweden. Unlike the previous studies discussed, Askanius and Hartley did not use individual high profile cases as bases for their research, opting instead for a two week period at the beginning of the movement in the US, from mid to late October 2017. Denmark and Sweden were chosen as two political contexts in which gender equality is a stated public goal that has been actively written into legislation and executive action for decades, yet notably both suffer from optimism on the state of gender quality in the countries that differs significantly from the lived experiences of the women in those countries. Whilst Askanius and Hartley (2019) found somewhat more pronounced in Danish coverage, media coverage in both countries maintained an individual level focus, framing sexual assault as a personal problem and treating survivors in many the same ways as the other studies in this section had found.

Where all the scholarship hitherto discussed leaves a gap, is the treatment of #MeToo media coverage internationally. They have either sampled specifically on one case (Hindes & Fileborn, 2019; Orgad & Gill, 2019), from a limited selection of news sources (Cuklanz, 2020), or with singular geographic focus (Askanius & Hartley, 2019; J. Lee, 2020). Only Lee attempted a comparison before and after the rise of the movement. If #MeToo is

indeed to have been a global phenomenon and the traditional media an active agent in the capture of attitudes towards sexual assault and violence, then a larger study employing quantitative computational social science methods is required. This study seeks to address this gap.

4.2.4 Computational Approaches to Framing

There have been numerous approaches to the analysis of framing computationally, rising with the increasing availability of online media and data alongside computational methods. There are in general three computational approaches to text analysis: lexical-based, supervised machine learning, and unsupervised machine learning. Lexical-based methods use pre-defined lists of words and their known associations, for example the word 'happy' in association with a 'positive' sentiment or outlook. Though most interpretable, these approaches can also be quite rigid in their application and does not allow easily for expansions beyond a single language, or the languages in which a dictionary is constructed. More critically for our purpose, rape myths and misconceptions about sexual assault often cannot be categorized solely on the basis of singular words. For example, 'He lied' and 'She lied' can have vastly different contexts, implicit assumptions, and pragmatic usage, none of which are captured in the use of 'lied'.

Unsupervised machine learning models often indicate a clustering method, whereby individual documents are clustered together in the hopes that the patterns thereby revealed can serve as an engine of discovery. Unsupervised approaches do not supervene upon theoretical underpinnings in the way supervised approaches do, and therefore given the aims of this study are unsuitable methodologically. Additionally, scholars have noted that unsupervised methods often also return a noticeable and important distance between the frames generated by computational analysis and those manually produced by our human analysts. The details of each method have a substantial impact on frame quality and interpretation. Nevertheless, they have proved fruitful in other contexts (Nicholls & Culpepper, 2020).

Supervised machine learning approaches automate the coding of predetermined frames (Matthes & Kohring, 2008). They are able to draw on theoretical insights to structure expectations about frames, which can generate powerful insights. Models are trained on sample of documents that are already labeled with the 'correct' answer. More recent approaches in the last few years have used transformer based models such as Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019). We use a variant of BERT belonging to this family, further described in the Methods section below.

More generally, supervised approaches have been the topic of a number of consistent criticisms. First, as already mentioned, though having become increasingly common over the last few years, computational methods

to framing analysis suffer consistently from criticism that it is not sufficiently theory-laden (Hilbert et al., 2019). Indeed, the concept of a frame can be fuzzy and has been criticized (Cacciatore et al., 2016). Scholars have also noted that though there is an increase in computational methodology, this has not necessarily equated to an increase in interdisciplinarity: no computational methods are not drawing sufficiently from theoretical frameworks and understandings of other disciplines (Hase et al., 2023). Second, supervised approaches are unable to offer insight into what frames might exist in a dataset, which theory has not already anticipated. This is most important when dealing with very large collections of texts from diverse news sources, where it is equally difficult for the researchers to manually analyze a large enough part of the collection to provide candidate frames which are representative of the whole dataset. Third, multilingual analyses are underdeveloped in framing analysis (Guo et al., 2023).

This study addresses each of these drawbacks in the following ways. The first is addressed insofar as the frames, or categories, that will constitute the classification task the models are trained upon are drawn up from a careful consideration of feminist scholarship that has approached media text through a critical and detailed lens employing content, thematic, and discourse analyses. These categories are drawn clearly from non-computational disciplines and methodologies. The second drawback is acknowledged as an inevitable limitation; however, we intentionally sampled through multiple languages and across over half a decade in media reporting to attempt to mitigate too narrow of a spotlight. We also kept open the possibility during the qualitative coding the possibility of identifying new codes. The third criticism is addressed both in the multilingual annotation process but also the modeling that draws from a language-agnostic transformer model that encodes semantic meaning across 109 languages (Feng et al., 2022).

4.3 Research Questions

Our central research question was the following: what was the impact of #MeToo on the presence and frequency of rape myths in news media around the world? This can be broken down also into sub-questions:

1. Did countries in which #MeToo have an impact maintain those changes?
2. How does political openness affect whether or not there is an impact, if at all?
3. How does geographic proximity of the subject affect the presence and frequency rape myths?

4.4 Hypotheses

We adopted the following hypotheses:

1. Given previous work on coverage of social movements and protests under the 'protest paradigm' (Chan & Lee, 1984), we hypothesized that there should not be, on aggregate, a global effect of #MeToo on the presence and frequency of rape myths that is maintained. However, there has been evidence of adaptations on journalistic practice in response to the movement (Hollings, 2020).

2. On at least one measure of political openness, a higher political openness will at least partially explain the variation between countries that do and do not have a significant change in the frequency of rape myths.

3. Greater geographic proximity should lead to a higher base level of newsworthiness assigned to stories, but also a higher conflict generated by the individual under scrutiny (Koopmans, 2004). These can influence and exacerbate existing media practices and generate higher levels of rape myths in the media.

4.5 Data

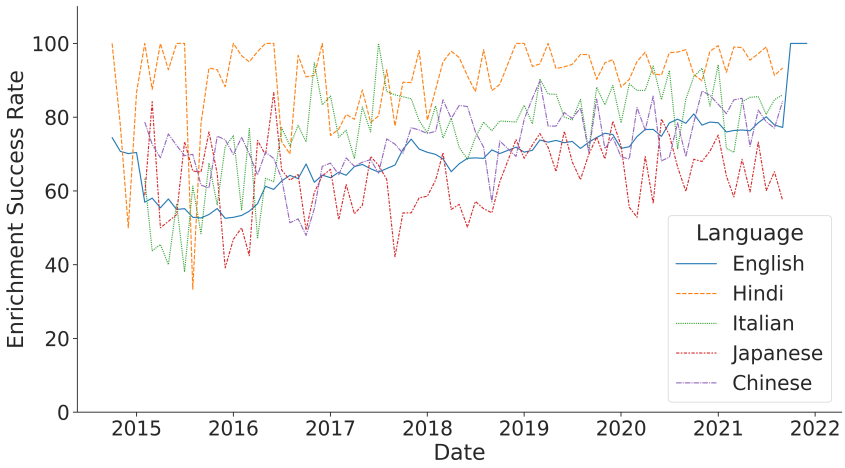
News media archives were obtained initially through Media Cloud (Roberts et al., 2021), a massive global open-source collection of online news. The search parameters were any news story between January 1st, 2014 and December 31st, 2022 that either included a mention of #MeToo or one of its known translations (see AppendixB.3), yielding 2,930,478 stories. Media Cloud stores references and URLs to the stories, but not the content of the stories directly. Therefore, the data needed to be 'enriched'. This enrichment was conducted using the newspaper3k[2] Python package, successfully retrieving 2,122,670 stories, an overall 72.4% success rate. The two languages with the most articles retrieved, English and Chinese, both had just over 70% enrichment rate. Figure 4.1 shows that these enrichment rates were largely consistent throughout 2014 to 2022 for the five languages with the most articles. These five languages account for 99.0% of the articles in the enriched data.

Subsequent to the enrichment, several further steps were employed to improve and ensure the data's reliability, consistency, and relevance. The first step taken was to eliminate redundancies within the dataset. This process included removing redundant identifiers as assigned by Media Cloud and URLs. Second, duplicate articles were removed. For this, we obtained bag-of-words (BOW) representations of the articles and used Facebook AI Similarity Search (FAISS) (J. Johnson et al., 2019), a library for efficient similarity search and clustering of high-dimensional vectors suitable for handling large corpora, to identify the closest neighbors to each article. Random sample inspection was used to determine the similarity threshold over which articles were sufficiently close to be considered identical. All copies but one of each set of duplicates were removed. Third, we removed articles with a length of zero, indicative of missing or corrupted data. No maximum length was specified, meaning articles of all lengths, provided they were not empty, were considered valid for inclusion.

[2]https://github.com/codelucas/newspaper

Figure 4.1

Enrichment Success Rate for Top 5 Languages



Note. This figure shows the enrichment success rate for the languages with the most articles in the dataset, shown across the article creation dates. Enrichment is largely more successful in later years, though rarely falls below 50% in the least successful period in 2015.

BERTopic clustering was performed after redundancy filtering to identify and remove irrelevant clusters of articles, as well as to confirm that the remaining articles were relevant. This approach also enabled us to clean the dataset using contextually-aware document embeddings, rather than the bag-of-words representations used earlier for de-duplication. BERTopic generated 100 clusters. Of those, the largest cluster contained 45.6% of the articles, with the top associated unigrams (words) ranked by term frequency–inverse document frequency (tf-idf) being 'women', 'sexual', 'allegations', and 'said'): these appeared to be all articles relating to reports of sexual assault, and a random sample of the articles in this cluster confirmed the same. By far the second largest cluster was the 'uncategorized' category account for 39.7% of the articles. The top words associated with this cluster were 'police', 'sexual', 'Trump', 'court', and 'accused'. It appeared upon manual inspection of a random sample that these were also relevant articles and often about legal proceedings. The top words for the majority of the much smaller remaining clusters indicated that they were often about specific cases of public sexual allegations: for example, one cluster contained articles about Japanese articles relating to #kutoo–a version of #MeToo in Japan–and campaigns to reduce pressure on women to wear high heels at work. Other clusters were collections of pages that had text retrieved but were of a generic error message, such as 'broken link'. These clusters were removed. Through BERTopic clustering we were also able to confirm that relevant articles in a range in languages were present in the data.

At the end of the data cleaning process, 935,684 articles remained from 23,768 media sources. Each media source for the articles was assigned an associated country through their Media Cloud metadata. 871 media

sources were identified as having an international focus or no particular country with which its output is specifically tied to (for example, United Nations outputs), and 5,152 media sources had no metadata that assigned it either to one country or to an international scope.

4.6 Methods

4.6.1 Rape Myths

Table 4.1 shows the typology of rape myths used in this work. The categories listed are all drawn from existing typologies in psychology, communications, and feminist scholarship. Numerous examples of this documentation occurs in the literature explicitly concerning rape myth acceptance in the public (Benedict, 1993; Brownmiller, 1975; Burt, 1980; Feild, 1978; Ward, 1988), but also amongst communications research on #MeToo media reporting that has surfaced and examined in detail the deployment of rape myths (Cuklanz, 2020; Hasunuma & Shin, 2019; Hindes & Fileborn, 2019; Orgad & Gill, 2019; Silveirinha et al., 2020).

We carefully compared and compiled these preceding contributions and codifications of rape myths into the present list. A few desiderata were imposed: first, that a myth should have appeared in more than one publication; second, that there was a sufficiently clear description of what qualified as an instance of that myth; third, that the myth has been found to appear in media text; finally, that the myth should be detectable in principle by a trained language model.

In some cases, different scholars employed slightly divergent categorizations from one another, and our table represents our attempt to select and unify the typologies across authors into a coherent set. For example, Lonsway and Fitzgerald (1994) discuss the myth that only 'certain' women such as those who have a 'bad' reputation or are from a minority group are raped. Other scholars speak of a similar myth and practice of 'objectifying victims' (Kitzinger, 2009) by suggesting for example what women wear might indicate what 'kind' of woman she is and therefore how much sympathy should be given. Still other scholars group this under 'scrutiny to the complainant' (Silveirinha et al., 2020) which can include casting doubt on the survivor's memory of the incident. Clearly, there is significant overlap between these classifications. In order to arrive at the final list we selected the the most discrete versions of myths, adding additional ones to complete the conceptual coverage where necessary: in this case, it gave rise to the 'Attacking Survivor' and 'Deserving of Assault' myths in Table 4.1.

In most cases, however, we found that same myths have been repeatedly identified by scholars across the many decades of research into rape myths.

The table should not be considered exhaustive, but rather a consolidation of myths whose construct validity has been thoroughly explored and tested by the extensive literature on the origin, acceptance, function, and dangers of rape myths from which our list is drawn.

Table 4.1

Table of Rape Myths

Myth	Short Name	Description
Assuming Survivors Lie about Sexual Assault and Rape	Lying	A common refrain to claim that survivors lie about rape and sexual violence for any number of reasons: to cover up an affair, to gain money or special treatment, because she was or is desperate or unstable, because it was a fantasy (Benedict, 1993; Lonsway & Fitzgerald, 1994).
Victimized perpetrators, or emphasis on professional status	Victimized Perpetrators	Placing large or undue emphasis on the professional, reputational, or personal damage being accused of sexual assault or rape can have on the perpetrator (Silveirinha et al., 2020).
Blaming external or contextual factors	External	The assumption that survivors should not have put themselves at risk due to factors external to the perpetrator, most typically alcohol (O'Hara, 2012).
Assuming sexual violence is only heterosexual	Heterosexual	Sexual assault and violence is assumed to only occur in heterosexual encounters, rendering non-heterosexual sexual assault and violence less visible and legitimate. (Mortimer et al., 2019).
Lack of guilt	Lack of guilt	Simple denial because sexual violence or rape is only perpetrated by 'strangers in dark alleys'. e.g. Cristiano Ronaldo's 2009 case (Silveirinha et al., 2020). Or that men go and have a good time and find themselves 'in a situation they can't control', hence absolving him of responsibility. Or that women are 'predatory' (Dwyer et al., 2012)
Attacking the survivor	Attacking survivor	Attacks on the lifestyle, actions, or perceived attributes of survivors to diminish them in some way. (Benedict, 1993; Kitzinger, 2004).
Only 'certain women' are sexually assaulted or raped	Deserving of Assault	Descriptions of survivors or suggestions that, for example, what someone wears, whether they were a 'tease', or are promiscuous and therefore deserving or 'asking for it' (Brinson, 1989).
Normalizing/Gaslighting	Normalizing	Claims, explicit or implicit, that sexual pressure and coercion are par for the course. How else are men supposed to act? (Hindes & Fileborn, 2019). It was just 'bad sex', or the survivor 'misread the mood'.
Downplaying seriousness of sexual assault	Trivializing	Claims that particular sexual assaults or rapes, or in general, are no big deal and are blown out of proportion by survivors speaking out (Silveirinha et al., 2020).
Perpetrators can only be monsters	Monsters	Language that assumes or promotes the idea that sexual assault only comes from monsters unknown to survivors that are 'brutish male aggressors' (O'Hara, 2012), rather than people survivors already know.

Continued on next page

Table 4.1 – continued from previous page

Myth	Short Name	Description
Valorizing the perpetrator	Valorizing Perpetrator	Celebrating or otherwise valorizing the actions of the perpetrator, for example framing Julian Assange as a 'sexy outlaw' (Harrington, 2018).
Women scorned	Women scorned	Claims that survivors, especially women, commonly make malicious rape accusations out of jealousy or hatred (Harrington, 2018).
Feminism 'gone too far'	Feminism	Assertions that feminism, especially under #MeToo has 'gone too far' and is the result of overzealous feminists. Potentially also assertions that there is an epidemic of false allegations (Trott, 2020).
Legal threshold	Legal	An undue emphasis on the legal thresholds of harm or seriousness concerning sexual violence, thereby rendering mundane, unimportant, or invisible much more everyday violence (Kitzinger, 2004).
Othering	Othering	The suggestion that someone sexually assaulted a survivor because they are of a different race, not cis-gendered, etc. (Lukose, 2018; Phipps, 2021).

Note. This table shows the rape myths synthesized from feminist scholarship and used for annotation. Short names indicate abbreviations used in text and in diagrams.

4.6.2 Annotation

The development of an effective machine learning model for the detection of rape myths in news articles necessitates a robust annotation methodology. This study's methodology began with the initial curation of rape myths from feminist literature, resulting in the identification of 16 distinct categories. These categories were then input into *Dedoose*, a collaborative annotation software that facilitated the annotation process across multiple languages, including English, Chinese, and Spanish (SocioCultural Research Consultants, 2021). We elected not to use crowd-sourcing tools such as Amazon's Mechanical Turk or Prolific as we wished for the labels all to be of high quality; moreover, conducting the qualitative coding for the categories discussed often requires discussion between coders. Indeed, the subject or even existence of rape myths is considered controversial - so much so that scholars speak of rape culture (Gay, 2018). We were not confident that we would have sufficient control over the annotation process. Further, it is impossible to consider the creation of new categories in a crowd-sourced setting.

A sample of 1,300 articles was then selected for annotation, with equal distribution across all years in the dataset. Annotation was carried out by the two co-authors, myself and Joana Perrone (cf. Appendix C): I annotated in Chinese, Joana annotated in Spanish, and we both annotated in English. To ensure consistency between We collaboratively constructed the codebook beforehand, and to we defined a set of 150 English articles that

we would both annotate and compare (Krippendorff's alpha of 0.856). Thereafter, we discussed the cases of disagreement and came to a consensus on each one. This introduced some changes: (a) the category of 'Othering' was added to capture the marginalization of survivors, while the assumption that survivors were exclusively women was discarded to accommodate a more comprehensive understanding of rape myths; and (b) we added clarity to some categories that were sometimes close such as blaming external factors and attacking the survivor, coming to a consensus on what we would look for thereafter individually in the annotation process. Notably, in the overlap there were also cases where we both agreed that entire articles seemed to contain latent rape culture attitudes but without a clear enough sentence that exhibited a particular rape myth in our codebook. No rape myths were annotated in such articles as we were working towards sentence-level models. There were only 3 such articles in our overlap sample of 150 English articles.

The annotation process resulted in around 200 annotations across the 16 categories. However, this quantity of annotations was deemed insufficient for effective machine learning. Consequently, the researchers employed data augmentation techniques using GPT-4 to generate additional data points for model fine-tuning, following a recently proposed approach (Møller et al., 2023). This step not only bolstered the dataset's size but also enhanced its diversity, allowing the model to more accurately detect and classify rape myths in news articles. The instructions provided to GPT-4 for data augmentation is provided in section B.1.

The annotation methodology applied in this study leveraged feminist literature to identify rape myths, employed collaborative annotation software, and adapted the categories as the research progressed. The approach ensured a comprehensive representation of news articles and incorporated data augmentation techniques to improve the machine learning model's accuracy in detecting rape myths. This rigorous process contributes to the development of a robust and effective tool for assessing news articles and advancing the understanding of rape myths in contemporary media.

4.6.3 Modeling

The research employed a detailed methodological process to fine-tune machine learning models for detecting rape myths in news media. As part of the annotation process, we annotated irrelevant articles that remained even after the rigorous data cleaning procedure. This dual-focus approach allowed us to train two distinct models: one to identify relevant sentences within the text and another to classify those sentences based on their content.

Contrary to Field et al. (2019), our approach did not adopt an entity-centric analysis. We aimed to identify rape myths in news media, a process requiring the consideration of broader context beyond single words or subject-object-verb triplets. Rape myths, as identified by scholars, often need comprehensive understanding of

a sentence or a paragraph to be properly recognized. However, we utilized the idea of annotating a small dataset and scaling it to a larger one as demonstrated in their study.

Similarly, while the work of Lucy and Gauthier (2022) provided valuable insights, we chose not to implement a word-level contextualized analysis. The nature of rape myths and their manifestation in language necessitates a broader scope of analysis, often requiring additional contextual words to maintain the integrity of the message. A narrowed focus would risk losing these crucial signals.

After the annotation and data augmentation processes, the Language-Agnostic BERT Sentence Embedding (LaBSE) model was used for fine-tuning. Though not necessarily the state-of-the-art, LaBSE's inherent support for multiple languages made it a suitable choice for our research, which spanned across Chinese, English, and Spanish. It's crucial to note that pure accuracy was not the central goal of our study, but rather a broader understanding of rape myth representation in news media. Today Large Language Models (LLMs), and decoder models more generally, have become prominent in natural language processing. However, we opted to use a BERT encoder-based model with the assumption that encoder models have displayed superior performance when used for classification tasks (Boitel et al., 2023), and also because generative LLMs typically do not produce consistent outputs, which would have introduced an additional methodological wrinkle that may not have contributed to the analysis. This is further discussed in the conclusion.

The resulting dataset consisted of a training set consisting of 1,096 news stories. However, some categories —Othering, Monsters, [assuming assault is] Heterosexual, and Legal —were discarded during the fine-tuning phase due to a lack of sufficient annotations. This is not a reflection of their analytical insignificance, but merely a constraint of the available data.

Utilizing these annotations, we categorized the complete dataset into relevant and irrelevant sentences. Relevant sentences were further classified based on their association with a relevant rape myth. To maintain a focus on high-confidence results, we set our classification boundaries higher than usual; more details regarding this decision can be found in the Appendix. In summary, our approach allowed for the nuanced detection and classification of rape myths in news media, while acknowledging the complexities inherent in such analysis.

After the modeling, we use Bayesian time series analysis to identify the impact the movement had in countries on the frequency of rape myths in the media. This is described in the following section. This time series analysis then enables not only a determination on a causal effect of the movement in each country, but also thereafter to determine whether political openness can explain any observed differences between countries through regression.

Finally, an examination of how geographic proximity can affect the representations in media is conducted as an exploratory and illustrative aspect of this methodology.

4.6.4 Political Opportunity Structures

To operationalize political opportunity structures, we draw upon a number of Varieties of Democracy (V-Dem) indices to capture the variations in political opportunity structure across the countries examined (Pemstein et al., 2023). V-Dem indices provide a broad range of measures that can be effectively utilized to operationalize the concept of political opportunity structure or political openness. In this study, we focused on several specific indices to capture various facets of this complex phenomenon. As described above, political openness is theorized to explain some variation in the course and impact of social movements.

The *Women's civil society participation* index was used to measure the level of political inclusivity. This index reflects the extent to which women are able to engage in public debate, associate freely, and play a meaningful role in civil society organizations. Greater civil society participation we might expect to lead to a greater impact on media coverage.

The *Women's civil liberties* index captures the extent of women's ability to make meaningful decisions in key areas of their lives. A greater ability to make meaningful decisions in key areas may mean a greater ability to challenge patriarchal norms and understandings about sexual violence.

The *Women's political empowerment* index was the next index. Women's political empowerment is defined as a process of increasing capacity for women, comprised of three equally-weighted dimensions: fundamental civil liberties, women's open discussion of political issues, and the descriptive representation of women in formal political positions. By encoding the level to which women hold political power in practice, a higher level of this index should indicate a higher level of agency and therefore alteration in the substance and process of media coverage.

The *Freedom of discussion for women* index, which measures the extent to which women are able to openly discuss political issues in private homes and in public spaces. In particular, it asks whether women can openly discuss political matters at home, in the workplace, and in other public spaces without fear of retribution. A higher degree of this freedom, we can hypothesize, should lead to a greater ability to challenge and affect the presence of rape myths in the media.

In addition to indices specifically concerning women's participation and empowerment, we also incorporated several indices concerning media control and structure to capture the variation in political openness in that

regard.

The *Centralization of media control* index measures the extent to which the media is centralized under and can be regulated by the regime. High media centralization can hinder political openness by limiting the diversity of viewpoints and information available to the public.

Both *Government censorship effort* and *Internet censorship effort* indices assess government censorship efforts on media and the internet, respectively. These indices highlight the impact of governmental control on the free flow of information, an important aspect of political opportunity structures: we would expect lower values of these indices to correlate with greater possibility of change in media representations.

The *Print/broadcast media critical* and *Print/broadcast media perspectives* indices look at the degree to which print/broadcast media is critical of the government and the range of perspectives that the media presents, respectively. These are significant indicators of media independence, and we would expect a higher level of media independence to mean a greater level of potential change in media representations.

Finally, the *Media self-censorship*, *Media bias*, and *Media corrupt* indices measure aspects of media separate from the government. Media self-censorship captures the extent to which journalists self-censor when reporting on politically sensitive issues, which can often be the case when politicians are involved in the #MeToo reporting. Media bias refers to bias against opposition parties or candidates. Media corruption measures the level of payments accepted by journalists to alter outputs. Higher levels of all of these would potentially impede change to the presence of rape myths in reporting.

Together, these indices provide a comprehensive and nuanced framework for understanding the political opportunity structure or political openness within a given society. By operationalizing these complex concepts using these indices, we are able to capture the multidimensional nature of political opportunity structures in our analysis.

4.6.5 Time Series Analysis

The outcome the propagated labels allows us to examine the trend of rape myths across time and geographies. In order to address whether #MeToo had an impact in individual countries, a Bayesian Structural Time Series was employed. A Bayesian approach allows for a formal way to incorporate prior information that is often possessed before seeing the data. Time series analyses are appropriate for their ability to account for temporality in the data. *Structural* Time Series, in particular, are used here because they are set up in terms of components, such as trends, seasonal components, and cycles, all of which have a direct interpretation. Therefore, in addition to the

forecasting that time series are often used for, they can provide a description of the main features of the series (Harvey, 2009).

Furthermore, the modular nature of structural time series also allows for the explicit modeling of intervention, or the effect of an external event. This naturally lends itself to application to examining the effect of the #MeToo movement on the presence of rape myths around the global media ecosystem. Formally, Bayesian Structural Time Series (henceforth 'BSTS') allows the modeling of observed counts $\mathbf{y}_{1:n} = (y_1, ..., y_n)$ as a result of a latent state with added Gaussian noise of a given variance σ_y. Initial states and empirical priors can be specified. Given a particular time of intervention, the causal impact analysis consists of examining the difference between a generated set of counterfactual responses $\tilde{\mathbf{y}}_{1:n} = (\tilde{y}_1, ..., \tilde{y}_n)$, which yields a posterior probability density over what may be considered the temporal evolution of causal impact. The posterior predictive density is a joint distribution over all counterfactual data points, in contrast to a collection of pointwise univariate distributions.

For our context, BSTS allows a statistical method of determining whether #MeToo had an impact on the frequency of rape myths in news media. This methodology also allows specifying different intervention times for different countries, accounting for the different times at which #MeToo garnered significant media attention in different countries. These intervention times were empirically determined from the volume of media coverage, and the identified intervention times are show in in Figure B.4.

The model uses two components in each country: (1) coverage level, derived from the number of articles for that country and month, and (2) an auto-regressive recency effect, accounting for influences from previous data points. Both components have empirical priors which are provided to the model. The outcome of each time series model (before the subsequent intervention analysis) is the estimation of the most likely component mean and standard deviations across the time period modeled.

The modeling was executed using the TensorFlow Probability (Brodersen et al., 2015) and CausalImpact packages (TensorFlow Developers, 2023). The model formula was:

$$f(t) = \Sigma_{k=1}^{2} f_k(t) + \epsilon, \epsilon \sim N(0, \sigma^2) \tag{4.1}$$

where $f_k(t)$ represent the three components: a linear regression on the coverage level priors, an autoregressive component for the recency effect, and a local linear trend for the rape myth frequency.

It is not uncommon for structural time series to include seasonal components. This was not included here as there is no particular reason to expect seasonality in the sample of news reporting, even if there is a seasonality to overall reporting (e.g. Christmas in the Global North broadly, where there may be more articles about shop-

ping). There is little to suggest why there should be seasonality to news reports concerning sexual assault, rape, and violence, or the #MeToo movement.

4.7 Results

Of the 935,684 articles, 313,990 were detected to have myths. The results allow a rich story to be told. Table 4.2 displays the performance of model fine tuning with and without data augmentation. Models with augmentation uniformly performed better on both the binary relevance classification and the multi class substantive labeling. Models trained with data augmentation were used for the subsequent analysis.

Table 4.2

Fine-tuning Performance Metrics

Model	Metric	Score
Rape Myth (with augmentation)	Macro F1	**95.90**
Rape Myth (without augmentation)	Macro F1	51.67
Relevance (with augmentation)	Precision	**99.10**
Relevance (without augmentation)	Precision	96.70

Note. This table shows the comparison of fine-tuning performance with and without data augmentation. 'Rape Myth' models apply labels to sentences that have been identified as relevant through the 'Relevance' models.

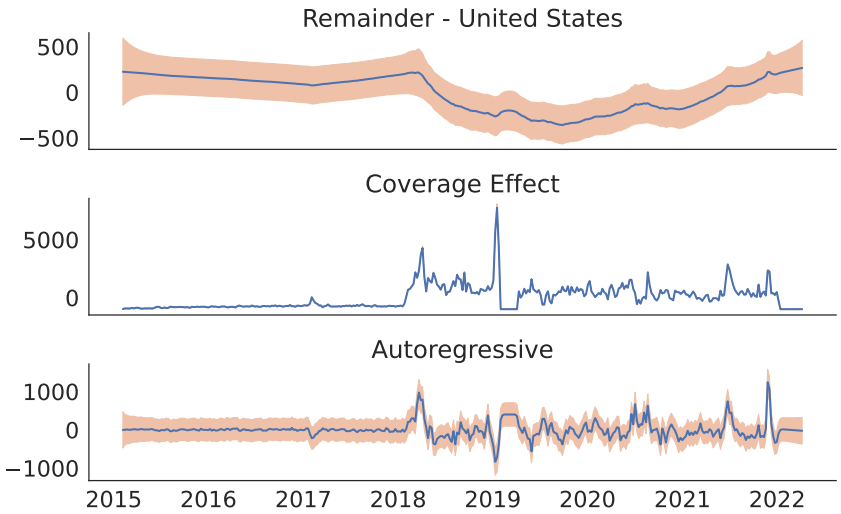
4.7.1 Time Series Analysis Results

For each country, the observed values $y_{1:n}$ were taken to be the total count of detected rape myths, grouped by month. An example of the the result of the modeling is shown Figure 4.2, where the bottom two plots display the extracted coverage effect and autoregressive effects respectively, and the top plot displays the remainder. This remainder can be understood as a measure of the frequency of the rape myths in the U.S. media. Some countries, like the U.S., showed a dip in the frequency of rape myths after 2017, but visually appear to return to pre-#MeToo levels by 2022. Figure 4.3 shows other countries, such as India, have a visibly different trend, and especially towards the later years in the sample, where India had its largest peaks in media coverage around #MeToo and sexual harassment and assault.

The intervention analysis for the U.S. is displayed in Figure 4.4. The post-intervention period was set at 1 year to strike a balance for there to have been enough time for any potential effects of #MeToo to take hold, whilst not being too long so as to lose that potential signal and also to limit the level of uncertainty post-intervention, which inevitably increases as with any time series analysis that has a prediction or forecasting component. The topmost plot in Figure 4.4 displays both the predicted and the actual data, with a vertical dotted line indicating

Figure 4.2

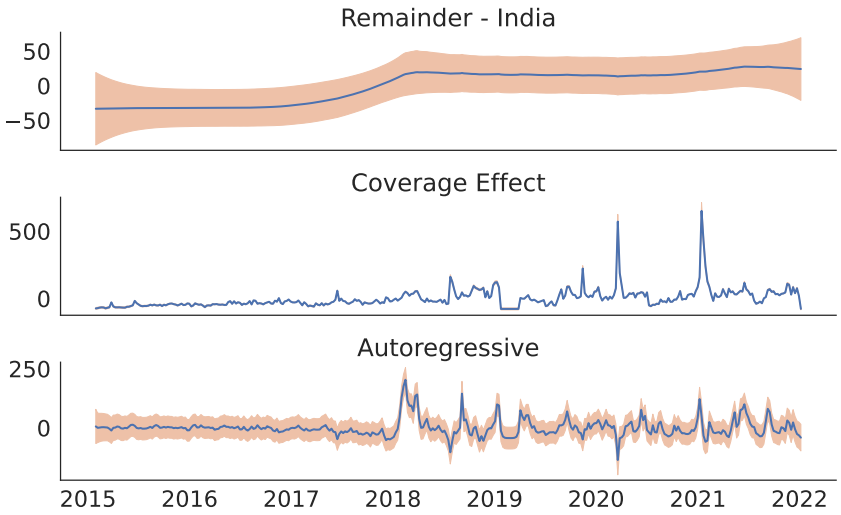
Time Series Breakdown of Rape Myth Frequency in the U.S.



Note. This figure shows the the breakdown of the time series of rape myth counts in U.S. media, aggregated by week. Blue lines indicate the mean value, and the orange area indicates variance. The middle plot displays the component of the time series that the volume of new coverage contributed, with little visible variance, and the bottom plot displays the autoregressive component or the recency effect of news coverage. The remainder, at the top, is the actual trend of rape myths in the media.

Figure 4.3

Time Series Breakdown of Rape Myth Frequency in India



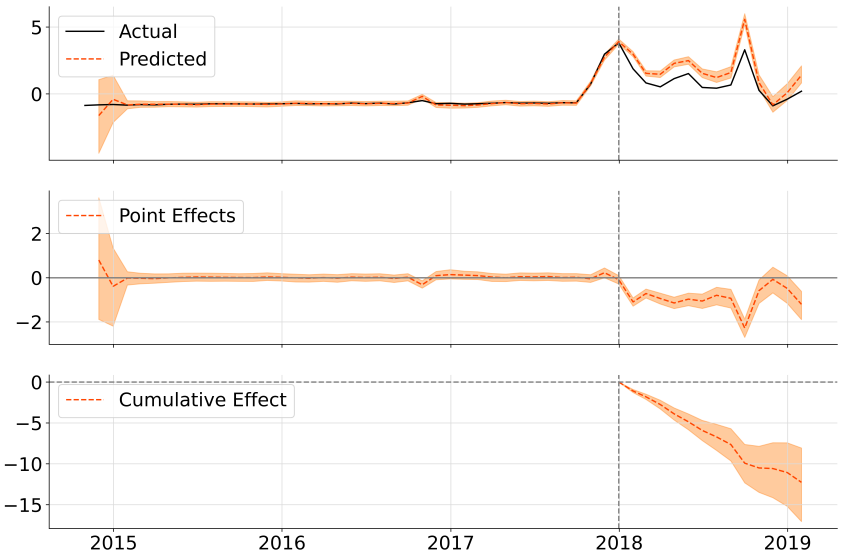
Note. This figure shows the the breakdown of the time series of rape myth counts in Indian media, aggregated by week. Blue lines indicate the mean value, and the orange area indicates variance. The middle plot displays the component of the time series that the volume of new coverage contributed, with little visible variance, and the bottom plot displays the autoregressive component or the recency effect of news coverage. The remainder, at the top, is the actual trend of rape myths in the media.

the date of intervention. The middle plot displays the differences between the observed and predicted values in the topmost plot, thereby indicating the point effects, which are the difference between the predicted and actual values at each time step. The bottom most plot displays the cumulative point effects after the point of intervention. For the U.S., the #MeToo movement had a negative effect on the frequency of rape myths appearing in news reports at a 5% significance level ($p < 0.001$) with a relative effect of -0.55, meaning that, after the #MeToo movement, the frequency of rape myths in U.S. media decreased by by 55% (95% posterior interval $[-77\%, -36\%]$). Media reports in South Korea, conversely, indicated no effect on the frequency of rape myths ($p = 0.09$) as shown in Figure 4.5.

A simple robustness check with intervention dates set to mid 2016 demonstrates comfortably that no countries had statistically significant intervention effects in the years before #MeToo: that is, there was no effect influencing the frequency of rape myths from 2014 to the beginning of the #MeToo movement in the US.

Figure 4.4

Intervention Analysis for the U.S.

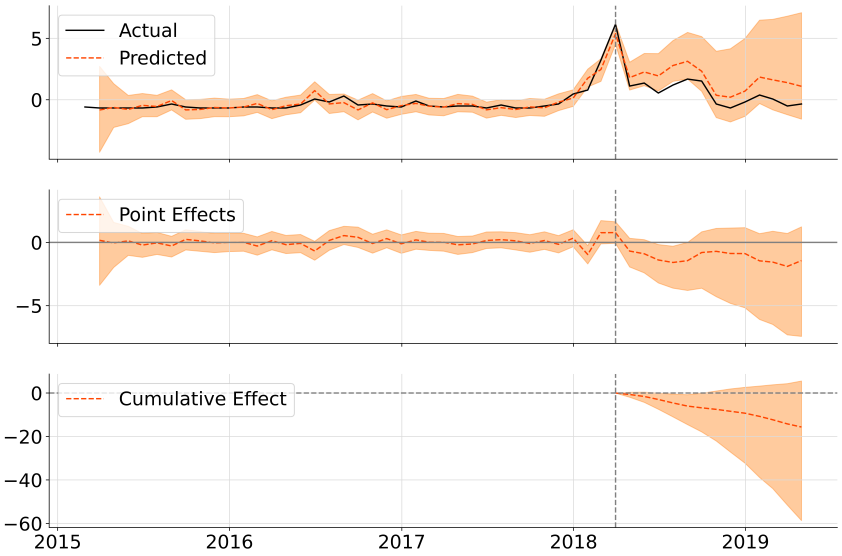


Note. This figure shows a visualization for the U.S. of Bayesian Structural Time Series Intervention Analysis. Vertical axis display normalized rather than absolute values of time series observations. The vertical dotted line indicates the time of intervention, i.e. the advent of the #MeToo movement for the country in question. The shaded region indicates model uncertainty around predicted values. The top graph displays both actual and Bayesian predicted values; the middle graph displays the individual data point effects due to the intervention; the bottom graph shows the cumulative values of point effects after the intervention.

Globally, over all countries with contributions weighted by volume of coverage and assuming an intervention date of October 15, 2017, the #MeToo movement had a relative effect of -0.22 a year after the start of the movement ($p = 0.03$). This means that globally the #MeToo movement lowered the frequency of rape myths in the media by 22% (95% posterior interval $[-50\%, -1\%]$).

Figure 4.5

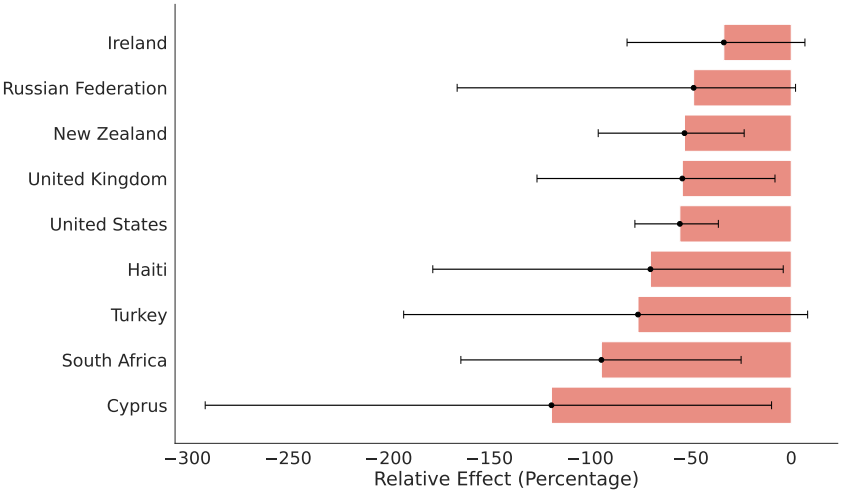
Intervention Analysis for South Korea



Note. This figure shows a visualization for the U.S. of Bayesian Structural Time Series Intervention Analysis. Vertical axis display normalized rather than absolute values of time series observations. The vertical dotted line indicates the time of intervention, i.e. the advent of the #MeToo movement for the country in question. The shaded region indicates model uncertainty around predicted values. The top graph displays both actual and Bayesian predicted values; the middle graph displays the individual data point effects due to the intervention; the bottom graph shows the cumulative values of point effects after the intervention.

Figure 4.6

Relative Effect Sizes for Countries with Negative Intervention Effects



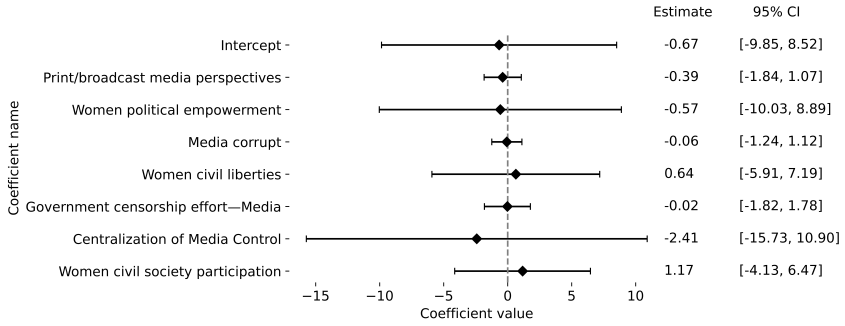
Note. This figure shows the relative effect estimates for countries with significant negative intervention effects. Error bars indicate 95% posterior intervals.

Figure 4.6 shows the 13 of the 47 countries (27.6%) for the analysis conducted resulted in nonzero effects at the 5% significance level, of which 9 were negative. In evaluating the relation to political openness, measures of political openness exhibited very little correlation with the either the relative effects or whether there was an effect. Figure 4.7 shows the point estimates and confidence intervals for the political opportunity indices.

To answer whether any measure, or combination of measures, of political openness play an explanatory part in the effect #MeToo had on the frequency of rape myths in the media, a logistic regression was run. This logistic regression had, as the dependent variable, the detected causal impact of #MeToo from the BSTS intervention analysis. The independent variables were the V-Dem indices, and a forward stepwise search was conducted to obtain the most informative model on the Akaike Information Criterion (AIC). Notably, in the final model on the forward stepwise search, there was not enough evidence at the 5% level to indicate that any of the gender-specific related indices—Women's civil society participation ($p = 0.67$), Women's civil liberties ($p = 0.85$), and Women' political empowerment ($p = 0.91$)—had nonzero coefficients, i.e. had any power in predicting the effect of #MeToo on the frequency of rape myths in news media. Moreover, no index of political openness predicted a significant change in the frequency of rape myths in the countries sampled.

Figure 4.7

Point Estimates for Coefficients of Political Openness



Note. This figure shows the point estimates for indices of political openness as explanatory variables for whether countries exhibited a non-zero change in rape myth frequencies in response to #MeToo. No evidence for coefficients being non-zero was found from this regression.

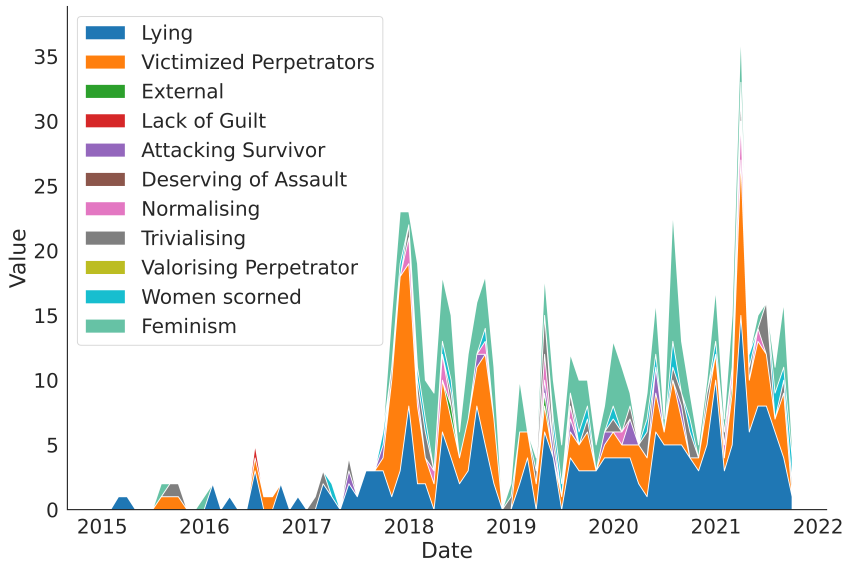
4.7.2 Comparison between categories of rape myths

The detected rape myths in the media were not evenly distributed. By far the most common labels were (a) assuming survivors lie about rape, (b) the victimization of perpetrators, and (c) that feminism had 'gone too far'. Examples of this are displayed for the Japanese context in Figure 4.8 and in the United Kingdom in Figure 4.9 respectively. This detected distribution was global. Further, these differences are not simply due to the distribution in training data leading to a likelier classification of these classes. The distributions of labels and

training data were distinct on a chi-squared test ($p < 0.001$). It appears that for the vast majority of countries, the assumption that survivors are lying and the victimization of perpetrators are dominant, consistent with repeatedly consistent findings of the literature (Burt, 1980; Franiuk, Seefelt, Cepress, & Vandello, 2008). The next most common myth is feminism having 'gone too far', and in particular gaining greater share of the distribution of myths at a given time after 2017 for both the UK and Japan displayed here, though remaining true of most other countries as well. This finding is also consistent with previous work (Worthington, 2020).

Figure 4.8

Detected Rape Myths in Japanese Media



Note. This figure shows a stacked area plot of detected rape myths in Japanese media. Lying and Victimized Perpetrators remain the most common throughout.

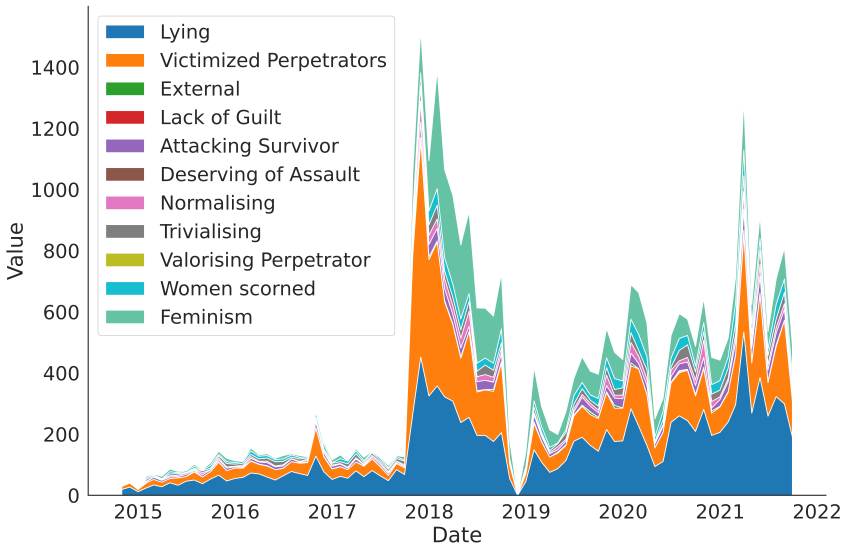
4.7.3 Geographic Proximity: Individuals

The methodology employed also allows a more granular approach to the analyzing media coverage and its variation with geography. Some of that variation might have expressed through different coverage of allegations of sexual assault against public figures. This section shows a few examples of how our methodology can be applied to such individual-level analysis, but is not intended to present an exhaustive picture - a more systematic analysis would require potentially accounting for many individual case specifics and might not account for the differential role and impact individual cases might have for the #MeToo movement in a given country. Instead, we hope to gain some insight into the impact of geographic proximity through case studies from around the world.

Figure 4.10 shows the patterns of coverage for the myth of Victimizing Perpetrators across the 5 countries with

Figure 4.9

Detected Rape Myths in U.K. Media



Note. This figure shows a stacked area plot of detected rape myths in U.K. media. Lying and Victimized Perpetrators remain the most common throughout.

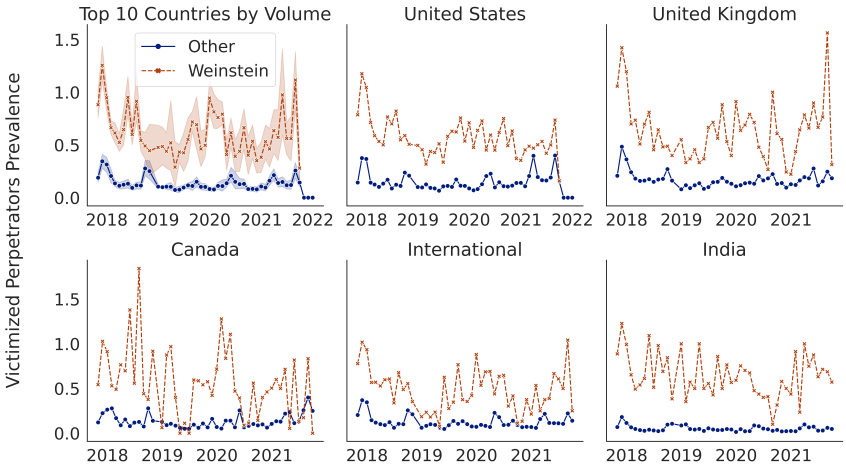
the most coverage of Harvey Weinstein. Coverage of Weinstein for all countries displayed exhibited higher levels of victimizing perpetrators than the average article in the dataset. This is perhaps unsurprising for higher profile figures who survivors speak out, as more emphasis can be placed on the consequences to the public figures' professional standing, and this effect may have been exacerbated with the particularly egregious nature of Weinstein's crimes and abuse of power coupled with his then prominence in the entertainment industry. Outside of a sharp spike mid 2018 in Canadian reporting, there is little variation across the top few countries for this myth. Though there is some geographic distance between the U.S. and the U.K. and India, it is also informative to contrast local coverage for Weinstein in the U.S. with coverage of him and the same events in a country both geographically distant and with major differences in its culture and political openness. Figure 4.11 shows the comparison between the U.S. and Egypt. The U.S. relatively consistent levels throughout the time period; in contrast, Egyptian outlets covered Weinstein less, though notably with higher prevalence of the Victimizing Perpetrators myth.

Weinstein was one of the largest figures associated with the #MeToo movement in both the U.S. and internationally, so may be a strong outlier in how news reports treated his case. Nana Patekar is a Bollywood actor who was accused by actress Tanushree Dutta of sexual harassment. Figure 4.12 shows the prevalence of the Lying myth in articles about Patekar. Interestingly, the leftmost plot showing the average of the top 10 countries by volume of reporting on Patekar indicate that the overall patterns for reporting on him did not differ greatly

from the averages of all coverage. This hold true for local media in India, but it is notable that in mid 2018 when allegations against Patekar began to surface, the prevalence of the Lying myth spiked most greatly in the U.S. media as opposed to local media, and again mid 2019 when a court verdict was reached for the legal proceedings corresponding to these allegations was reached.

Figure 4.10

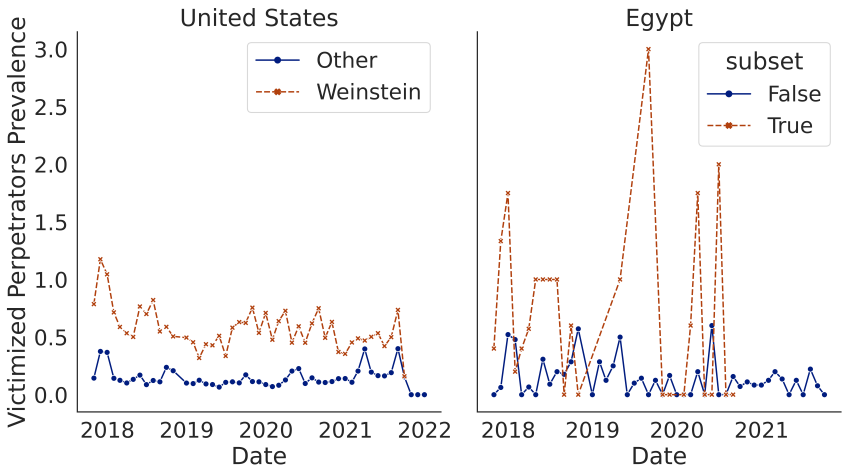
Prevalence of Victimizing Perpetrators Myth in Articles about Harvey Weinstein



Note. Prevalence here is defined as the average count of the myth in question per article.

Figure 4.11

Prevalence of Victimizing Perpetrators Myth in Articles about Harvey Weinstein in a Culturally Distant Context



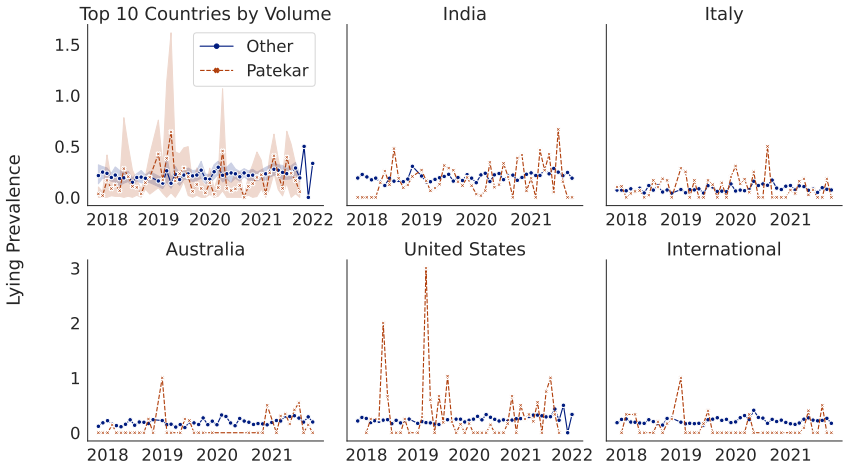
Note. This figure shows the prevalence of rape myths in articles about Harvey Weinstein locally–in the U.S.–in contrast with a politically and culturally distant context, Egypt. Such a technique may be useful in future to explicitly separate geographical differences in media representations.

For the Japanese #MeToo context, the prevalence of the rape myth of feminism having gone 'crazy' or 'too far' in the coverage about an accused individual is shown for Noriyuki Yamaguchi in Figure 4.13. Spikes occur

in the occurrence of the Lying myth at the end of 2019 when Shiori Ito was awarded damages in a court case, though notably in the US and China much more prominently than in the local context of Japan. Another spike occurred in 2021 when Ito published her memoir *Black Box*.

Figure 4.12

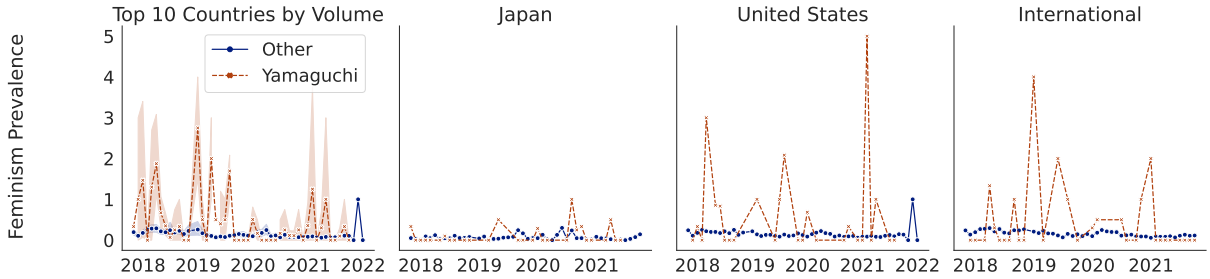
Prevalence of Victimizing Perpetrators Myth in Articles about Nana Patekar



Note. Prevalence here is defined as the average count of the myth in question per article.

Figure 4.13

Prevalence of Victimizing Perpetrators Myth in Articles about Noriyuki Yamaguchi



Note. Prevalence here is defined as the average count of the myth in question per article.

4.7.4 Robustness Checks: Substantive Labeling

A key part of the evaluation of the automatic label distribution throughout the dataset is how well the models were able to capture the different rape myths tabulated in Table 4.1. To determine this, a stratified sample of labeled sentences across each year and myth category was obtained and examined by the authors. The authors annotated the resulting samples in a ternary fashion: the labeled sentence could be correctly labeled, incorrectly labeled, or would require more context in order to decide.

Though the models performed well on training metrics, inevitably application on a wider range of languages

Table 4.3

Robustness Check

Myth	Correct	Incorrect	Context
Lying	0.61	0.20	0.19
Victimizing Perpetrators	0.56	0.32	0.12
External	0.13	0.75	0.12
Lack of Guilt	0.52	0.36	0.12
Attacking Survivor	0.46	0.52	0.02
Deserving of Assault	0.1	0.9	0
Normalizing	0.54	0.38	0.08
Trivializing	0.54	0.38	0.08
Valorizing Perpetrator	0.2	0.8	0
Women scorned	0.52	0.34	0.14
Feminism	0.46	0.4	0.14

Note. This table the proportion of each sampled machine labels annotated by authors as correct, incorrect, or requiring more context.

and variety of writing leads to a suffering of accuracy. In particular, the categories of External, Deserving of Assault, and Valorizing Perpetrators were categories where the model had learned the worst. This correlated with the categories that had the fewest training samples. Though these categories had the worst performance, they also accounted for fewer than 3% of the total myths labeled throughout the dataset, and therefore do not significantly change the analysis.

What is important to gauge, however, was whether there was any temporal pattern to the errors made by the model. On the stratified sample, it was no likelier for an error to be made in 2014 than it was to be made in 2017 or 2022, for example (Chi-squared $p = 0.52$). Therefore, important insights can still be gleaned from the data concerning the frequency of these myths over time given a systematic error.

Some examples of the different categories that were captured correctly are quoted here for illustration. The Lying, Victimizing Perpetrators, and Feminism myths often captured relevant and differently constructed instances of those respective myths than was present in the training data. One line that exemplified the Lying category was:

> *Tapper said: "Just to correct you, it's a she said, she said, she said, she said, she said, she said, she said, she said, she said situation."*

And a clear example of the Attacking Survivor category was:

> *Why couldn't you just keep your knees together?*

Assuming that survivors coming forward are typically women scorned, looking for revenge sometimes occurred

as:

> *Morani said the complaint was filed with the sole intention of tarnishing his reputation and image.*

One notable theme in the sentences that were incorrectly labeled by the models were ones that demonstrated the model's inability to consistently differentiate between sentences that were making claims about the state of society's attitudes towards sexual harassment and assault and how it under serves survivors, as opposed to ones that are grammatically similar but very different in meaning. Often, these might require more context outside of not just the sentence but of society more broadly to detect. For example:

> *She said: "This underlying current of sexism and abuse is the environment in which violence against women is endemic."*

Could easily have been

> *She said: "This underlying current of sexism and abuse is the environment in which violence against women is* ***nonexistent****."*

Semantic differences between 'nonexistent' and 'endemic' may be encoded, but only understanding—or at least encoded information concerning—the relationship between sexism, violence against women, and the history of harms would allow a model to consistently parse the difference correctly.

4.8 Conclusion

This paper set out to examine whether or not the #MeToo movement affected the representations of sexual assault, harassment, and rape in the media around the world as a global digital movement. This is critical as the media play an important role in shaping public conceptions of what sexual assault, harassment, and rape even consist of. One major aspect of such representation is the appearance of rape myths in the media, consistently documented in feminist scholarship as reinforcing patriarchal, anachronistic, and harmful notions about sexual assault. This study sought to examine whether the #MeToo movement globally affected the frequency of these rape myths by training machine learning models on specific categories of rape myths that have been documented and collected by the same scholars over decades, and using them to achieve an analysis at a larger scale than had been previously possible. This study examined 47 countries in which there was substantive reporting on #MeToo and associated public allegations of sexual assault.

In conclusion, we find that globally, there was a nonzero lowering effect on the frequency of rape myths in the media a year after 2017. However, much of this signal is concentrated in a relatively small number of countries

which had higher volumes of articles collected in the sample. When broken down by country and differentiated by the various dates at which the movement gathered momentum in each respective context, only 9 of the 47 countries exhibited this statistically significant lowering effect. Further investigating these patterns, we found that higher political openness did not mean media in those countries were more receptive to the messaging of #MeToo survivors speaking out about rape culture. Moreover, we found that where #MeToo did have a statistically significant impact, some of these (for example the U.S. as shown in Figure 4.2) show a tendency to have reverted back to pre-movement levels by 2022. Higher political openness has not explained whether or not a country's media was found to have a significant effect or not.

Finally, geographic proximity also plays a role, and we endeavored to show a few examples of around the world with Weinstein, Patekar, and Yamaguchi. Interestingly, on the examples chosen it was not the case that closer geographic proximity between the newsroom and the 'site' of protest increased the frequency of rape myths, but just the opposite. Though examined through selected case studies, the results nevertheless highlight interesting geographic differences that warrants further exploration. We hope that these methods also have the potential to better enable scholars investigating rape myths and culture.

4.9 Discussion

Rape myths are not the totality of how sexual harassment and violence are understood, publicly or privately, but they form a clear and consistent aspect of a patriarchal society. How media institutions employ them, intentionally or otherwise–given especially the complex relationship between media, social movements, and feminist activism where new media have influence over public conceptions of what even *constitutes* sexual violence–is therefore an important indicator of societal attitudes. Accordingly, we believe the most striking result of this article to be the resilience of media institutions around the world to even a 'global' #MeToo movement. Only a small minority of countries' media reduced the prevalence of rape myths in response to the movement, and some even reverted back to pre-2017 levels of prevalence by 2022. More alarmingly, political openness, triangulated using a litany of V-Dem indices, revealed that these measures provided sway over which media systems responded or not to #MeToo. That is, political regimes typically associated with higher openness to social movements and contentious politics were *not* likelier to have positively responded to change #MeToo called for, and conversely more closed political regimes that are less democratic and where governmental action greatly affects resources and activity within that regime, were *just as likely* to have positive responded. Therefore, we see yet another piece of evidence for not only the global ubiquity of rape myths, but just how **deeply seated rape myths are in media institutions, and how resistant to change these media institutions also are.** This raises impor-

tant questions about how individual activists and groups of challengers engaging in contentious politics with regard to digital activism should understand and interact with media coverage, ones we hope can be addressed in future scholarship.

Given the scope and abstraction inherent in the methodological structure of this article, details of political, social, and cultural differences between the countries included in analysis are lost to a degree. As mentioned in the Introduction, there are important differences between the sexual ethics, gender norms, and institutionalized attitudes towards sexual assault around the world (Flaskerud, 2019): #MeToo never arrives *ex nihilo* and without background context, though we contend it stands out enough as an individual instance of feminist activism that stretched across borders to warrant individual attention. Where this article hopes to position itself, then, is the complement of existing literature that can and does more adequately speak to these particularities. Sexual assault and violence against women knows no borders, and insofar as that is true this article uses that as the basis for abstraction and comparison across countries, to bring this horribly shared human experience into focus.

What is lost by such abstraction? First, and most importantly, research analyses necessarily adopt boundaries in conceptual and methodological construction that with a seeming 'objectivity' that organizes the world into sub-groups of data worth examining (Haraway, 1988). We recognize that our work is no exception, and emphasize that it sits alongside the collections of more detailed politically and culturally situated analyses and knowledge by social movement and feminist scholars. Second, such abstraction may impact our analyses operationally by the loss of confounding factors. That is, a deep understanding of the contexts studied here may have yielded important information, for example the impact of religion and society in more pious countries, the history of femicide and activism against it in Latin America, and more. We acknowledge all the foregoing and hope our work stands nevertheless with contribution.

4.10 Limitations and Future Work

Despite the significant insights gleaned from this study, it is crucial to acknowledge the inherent limitations and prospective areas for future work.

Methodologically, though the models performed well in training, the propagation of labels across the full dataset revealed that the External, Deserving of Assault, and Valorizing Perpetrator categories were the signals least picked up by the models. Though this effect did not significantly impact the analysis as these less than 3% of the propagated labels belonged to them, not all of this effect is due to the low volume of training data for these categories. One issue lies in the assignment of categories based on context. Often, the necessary context for imputing sentences or paragraphs to specific categories is absent, as was observed during the annotation

process. This naturally calls for future research to explore more context-sensitive approaches, though it is not always clear what the relevant context should be: for example, in some cases where more explicit language is used and the statements clearer, less context is necessary. In contrast, some text is subtler in meaning and often requires holistic consideration of not only the current paragraph or document, but an understanding of wider political and social contexts. These observations are precisely the domain of careful qualitative work, which this study did not seek to supplant but rather to augment.

Improvements to data cleaning may have been possible. Horne and Adali (2018) examine the practice of news media republishing articles, sometimes done by media institutions to fill content or make specific stories seem more important. This practice was not explicitly taken into account during data cleaning, though we believe that the de-duplication methods applied would have captured some of these media re-publication practices as Horne and Adali (2018) identified that content of articles–what we performed the de-duplication on here–was often identical with headlines changed in republishing.

Additionally, the delineation of the categories used in annotation in this study are not universal. One illustration of this is that the assumption survivors are lying may not be distinct from also assuming that the survivor wants to 'get back at' or seek revenge against the perpetrator (Burt, 1980). That is, the conceptual categories presented here are at minimum not always clearly demarcated, notwithstanding potentially different definitions and groupings that another approach may have resulted in. However, it is worth noting that collapsing some of the categories into the Lying myth, for example, would indicate that the current estimate for frequency of this myth is even further an underestimate.

Attributing media to a single country proved challenging, particularly for larger media sources like Reuters that cover multiple countries. The use of Media Cloud, though beneficial, introduces additional limitations due to its heavy skew towards English language sources. Future work could benefit from taking into account the differences between the publication practices of each media outlets and gather additional news sources for those less monitored by sources like Media Cloud.

Conceptual challenges also surfaced, such as how to operationalize metrics like the size of a protest, particularly in the context of a digital movement like #MeToo. Additionally, as mentioned above there are potential exogenous factors that could impact results, like femicide events that gain significant traction. This study assumed that the #MeToo movement remains at the forefront of journalistic output, an assumption which warrants further examination.

Lastly, the study operated on the assumption that exogenous drivers like #MeToo have enduring effects and are

not merely one-time interventions. This is a limitation inherent to any single-point intervention modeling and provides another direction for future research.

Chapter 5

Article III: Digital Collective Memories of #MeToo

5.1 Introduction

That the civil rights struggle in the U.S. is remembered to be peaceful and that the Hong Kong protests in 2014 are associated with yellow umbrellas is no coincidence: these memories of the past are constructed. Memories that are–especially in relation to social movements–often inextricably linked with moral and political significance and therefore whose construction often requires struggle and contention. Shared representations are not automatic outcomes of mobilized protest or digital activism, but are the result of 'memory work' (Jansen, 2007): the totality of deliberate effort including selection, exclusion, invocation of, and discursive practices to create and maintain collective memory.

Digital media, equipped with abundant availability, portability, and immediacy, enable new possibilities in what is archived, and *who* does the archiving (Hoskins, 2011). In contrast to the previous era, where broadcast media were dominant in determining shared representations that therefore partially constituted shared memory, digital media fundamentally alter what memory is and what memory does. Digital media opened up new ways of activism and contentious politics (Bennett & Segerberg, 2013) and has done the same for memory. Digital media offer the creation, the sorting through and the filtering of memories that go beyond institutionally and spatially bound archives that preceded it.

Three clusters of digital memory work of social movements have been identified by scholars (Merrill et al., 2020): these are curation (Katriel & Gutman, 2015), circulation (Smit et al., 2017), and claims (Florini, 2016). *Curation* indicates the deliberate internet archiving practices, such as in video form. This intentional archiving can come in many forms and is the most obvious and acknowledged by social movement and memory scholars (e.g. Caswell, 2015). Beyond curation, digital media also allows for opportunities to disseminate memory in more potent ways. *Circulation* describes this capacity. Finally, contemporary social movements also *claim* and frame

memories through digital media.

To examine these processes, this study adopts Burkey's (2020) conceptual and methodological framework to examine the three processes of memory production. First, this framework emphasizes the multimodal nature of memory practices, encompassing both multitude of ways users can create, interact, and participate in social remembering, but also the multitude of platforms and devices these multimodal practices occur. This conceptual framework contends that the way users choose and interact with digital platforms and social media in relation to memory defines what they wish to remember and how they want to remember it. At core, this is a practice of *privileging* certain narratives, platforms, content types, and people. Moreover, this privileging occurs across all of curation, circulation, and claiming mentioned above. Second, Burkey's framework foreground the understanding of *who* is producing the memories, and additionally who those memories are shared with. Finally, the framework highlights the utility of metadata in understanding digital memory practices.

With these clusters of memory work in mind, in this study we are interested in understanding how a prominent case of digital activism–the #MeToo movement–is remembered on digital platforms. We pose the question: how has #MeToo lasted through digital memories? The research question is posed with particular interest to the transnational nature of #MeToo. It is known that #MeToo has spread across the world (A. Park, 2017), but how has that translated to digital memories? Indeed, previous work on memory and movements on digital media have not often examined movements beyond the English-speaking world (Twyman et al., 2017). Though the intersection of memory and social movements is of increasing interest to scholars and has seen a growing body of work, few studies have examined the lasting of digital feminist movements like #MeToo, #SayHerName, and more, through digital memory across national contexts. Previous work have often either examined particular cultural repositories, memorials, etc. or examined Wikipedia exclusively (Grabowski & Klein, 2023; Twyman et al., 2017).

I used the technique of triangulation (Denzin, 1970) to answer the main research question and sub research questions that arise. This triangulation was conducted through three ways in which digital memory is constructed: curation, circulation, and claims with different media sources for each, and through Burkey's (2020) conceptual framework of examining digital practice.

To examine curation, I used two curated datasets of #MeToo digital content: the #MeToo Web Archive created by the Harvard Schlesinger Library and a subset of the Feminist and Queer Activist Movements in Transnational China and the Asian Diaspora archive, created the Ivy Plus Libraries Confederation. The former is a collection scoped to concern the U.S. #MeToo context, whereas the latter is scoped to #MeToo digital traces from the movement in China.

To examine circulation, I used TikTok as a dataset to examine circulation of #MeToo digital memory, as a hugely popular social media platform of video content. X, formerly Twitter, is not considered here as it has markedly changed from the platform that enabled #MeToo and other hashtag campaigns since it was acquired by Elon Musk, and has been well documented to surface misinformation, potentially antisemitic content, and cryptocurrency scams. These not only create more negative spaces for activists to circulate memories in relation to #MeToo there, but also means memories circulated are less likely to be surfaced. TikTok content is by no means exempt from the same algorithmic sorting, filtering, and surfacing that is opaque, but I contend X serves much poorer as a space for memory circulation on this basis.

To examine claims, I used Wikipedia across different languages to examine claims made about the #MeToo movement. Wikipedia is a unique data source for this aspect for a number of reasons. First, it has been identified by scholars as a locus of collective memory (Pentzold, 2009), and is often a secondary source of information on current events (P. Singer et al., 2017). Wikipedians do the work of classifying knowledge about the world (Ford et al., 2023), and therefore participate actively not only in knowledge production but also memory work. However, whereas there have been numerous quantitative studies on Wikipedia in relation to (e.g. Twyman et al., 2017; Yasseri et al., 2012, 2013), quantitative studies alone cannot identify Wikipedia's distortions, omissions, and evaluate intentionality and digital practices (Grabowski & Klein, 2023).

5.2 Background and Related Work

5.2.1 Why Memory Matters

The study of shared representations of past or current events, which has been referred to as 'memory', is important. In the first instance, we are interested in memory as a field of study because 'much of what we remember is actually filtered through a process of interpretation that usually takes place within particular social surroundings' (p.285, Zerubavel, 1996). Consider how we remember events that we know occurred but just before our lifetimes: those born after 2001 will not remember the Iraq War or the September 11 attacks, and therefore whose understanding of it necessarily stems from commemorative symbols and displays (such as the Ground Zero memorial in New York), narratives handed down orally or textually (through Wikipedia, for example), and more. These shared representations matter deeply for how the past is remembered and interpreted.

This area of research has most prominently been associated with 'collective memory', a term coined by Halbwachs (1980). For him, the collective is a function or a process of negotiation and mediation–typically the determination of aspects of a memorial–that acquires its *collectiveness* amongst those who take part in and ac-

cept the outcome of this process. Collective memory is understood, then, as the set of symbols and practices referring to the past which are shared by a community of people (Kansteiner, 2002). Interestingly, though it has since been associated or used to mean memory of society or social groups more generally, often with particular reference to broadcast media (e.g. Edgerton, 2020), Halbwachs made no explicit mention of broadcast or electronic media as sites of collective memory. This opens up a natural question on how electronic and digital media do relate to collective memory, to be addressed below.

Memory, whether 'collective', 'social', 'joint', or otherwise, matters for many applications, but matters in particular for social movements for a few critical reasons. First, movements are often described in news media or in political commentary as ahistorical, *ex nihilo*, and isolated, all of which are untrue upon any further examination (Daphi & Zamponi, 2019). Scholars have long observed, for example, that movement mobilization occurs in temporally aggregated waves and protests (McAdam, 1995; Tarrow, 2022). To take a simple illustration, 'revolution years' such as 1848, 1917, 1989, etc. where there intense mobilizations occurred across many countries and societies simultaneously: in 1989, protests in the East German communist regime played a role in sparking other Eastern European revolutions of that period, ultimately shifting global politics permanently with the fall of the Soviet Union (Koopmans, 2007). Second, scholars have identified some mechanisms that facilitate such connections of mobilization across time and space, for example through networks (Gould, 2003) and social movement communities (Buechler, 1990). Finally, as is the goal of many social movements, broader culture and societal attitudes can be influenced by their mobilizations, influencing public memory.

5.2.2 Memory-Movement Nexus

Public memory matters, and just as waves of mobilization are historically situated and are not isolated, the final elements that comprise public memory are not accidental, isolated, or without influence. Public memory is strategic for setting the criteria of plausibility and relevance: the perspective and narratives preserved and revisited impose legitimacy and symbolic power. It is a powerful cultural resource that can be used to build active movement communities, shape public understanding, and direct institutional policies. The constitution of memory as a process of selection, encoding, and storage is therefore a process that is subject to historical, psychological, and social influences: is 'as much as result of conscious manipulation as unconscious absorption and it is always mediated' (p.180, Kansteiner, 2002). It is a series of dialectic exchanges where actors simultaneously use the past to interpret the present and reciprocally the present to interpret the past. These public memories and shared representations, therefore, exists as something in continuous interactive development, repeatedly interpreted and reinterpreted through these interactive exchanges (Olick, 1999).

The contingent and crucially *contested* nature of memory therefore gives rise to an interdisciplinary nexus of research between memory and social movement studies (Hoskins, 2018b; Kubal & Becerra, 2014). Memory scholars have become increasingly interested in the agency that can and are exerted to influence memory, and social movement scholars have turned more attention to memory in light of debates of temporality and continuity between movements (Daphi & Zamponi, 2019). The part of of this literature that concerns this study the most is that concerning the memories of movements: how are certain events remembered, and additionally why are certain events or movements remembered? For example, scholars have studied these questions in relation to feminist protests (Chidgey, 2015), LGBTQ+ (Armstrong & Crage, 2006), and public commemoration of the civil rights movement (Polletta, 2006).

Though growing, it is not a well-integrated field of research, split amongst numerous frameworks, disciplinary backgrounds, and methodological approaches. This is illustrated by the fact that 'collective' memory is not even a term employed with consensus. Whereas collective memory was initially conceptualized around objects and physical symbols, more recent research has focused on public memory as this interactive process. This interactivity, and even *hyper-connectivity* (Hoskins, 2011), that digital media brings exacerbates these differences, causing some scholars to eschew the term 'collective' memory altogether. For clarity, I remain with the term 'collective' throughout the rest of this article.

5.2.3 Digital Media

How does digital media affect the production of memory? A full answer to that question would be beyond what is possible in this article, but a few important consequences may be highlighted here. The process and nature of archiving has previously been solely external and separate to the self, typically requiring institutional apparatus to house and display artefacts and curations that spark remembrance of the past. The hyper-connectivity we experience through the plethora of digital platforms and increasingly ubiquitous devices splinters the individual, cultural, and social imaginaries. Archives are not only curated and kept by institutions but are created in an active, living manner through the myriad affordances of digital platforms from YouTube and TikTok videos, individual blogs, public microblogging on Twitter, collaborative editing on Wikipedia, and more. The dividing lines between public and private are blurred. Further, the power of digital search and accessibility, little remains unseen or untouched: 'the past becomes what Everyman chooses to accept is true' (p.3, Lowenthal, 2012). In sum, the digital fundamentally transforms the potential of shared or public memory, fundamentally determining what can and cannot be remembered (Hoskins, 2018b). This is a new 'media ecology' that has led some scholars to propose moving beyond 'collective memory' as terminology more applicable in the broadcast era of mass media to the 'memory-of-the-multitude' (Hoskins, 2018a).

Importantly, though digital media does offer numerous new avenues to create and engage with memory, we are not contending that the digital presents a 'perfectly a neoliberal utopia of a globalized, borderless world' (De Cesari & Rigney, 2014). Much remains to be understood about how the impact of digital mnemonic practices–whatever they may be–impact movements and memory.

Thus far, digital memory practices are broadly split amongst three strands identified by Merrill et al. (2020): these are curation (Katriel & Gutman, 2015, e.g.), circulation (Smit et al., 2017, e.g.), and claims (Florini, 2016, e.g.). Where previous work have often focused on a single one of these processes, this study seeks to go beyond and examine datasets for each one.

As mentioned above, *Curation* indicates deliberate internet archiving practices. Examples include the recording of memories of Palestinian experiences at Israeli checkpoints (Ashuri, 2011), the curation of second-generation memory activism instigated by H.I.J.O.S. (Hijos por la Identidad y la Justicia contra el Olvido y el Silencio), an organisation comprising the children of those imprisoned and murdered by the Argentinian dictatorship between 1976-83 (Levey, 2020), or indeed one of the sources of data for this study: the Harvard Schlesinger Library #MeToo archive. This intentional archiving can come in many forms and is the most obvious and acknowledged by social movement and memory scholars (e.g. Caswell, 2015).

Circulation describes the capacity of digital media to reach and interact with activists, current and future, along with the general public. YouTube videos have been used to disseminate visuals of the Ghouta chemical attack in Syria that not only contributed to archives but also to 'show the world the atrocities of chemical warfare and move a global audience into action' (p.302, Smit et al., 2017). Elsewhere, the hashtag #ioricordo ('I remember') has been used to spread rememberance of the anti-G8 protests that took place in Genoa in 2001 (Zamponi, 2020). Specifically in relation to feminist activism, some scholars have found that the need to appear 'authentic and relatable' can adversely affect the way narratives and disclosures of sexual violence are presented on YouTube (Harrington & Gerrard, 2023, p.214).

Finally, contemporary social movements also *claim* and frame memories through digital media. For example, Facebook groups have been used to situate the police killing of Mike Brown within a broader mobilization against violence against Black people in the U.S (Smit et al., 2018). On Wikipedia, recent work has found that a handful of editors, with more dedication and fervor than can often be effectively checked in a community of volunteer contributors, consistently skewing the representation of the Holocaust on Wikipedia to a version touted by far-right Polish nationalists (Grabowski & Klein, 2023).

As an interdisciplinary area of research, memory has also been the subject of some research from computational

social science scholars, and Wikipedia has been on particular interest. Pentzold (2009) argued that Wikipedia serves as a global memory place, and is a major part of scholarship on digital media and memory. Luyt (2016) examined how different views of the Vietnam war was represented on Wikipedia. Ferron and Massa (2011) profile the collaboration and conflict of the editor network in documenting the 2011 Egyptian Revolution in multiple languages. More quantitative analyses have identified the role Wikipedia entries play in resurgent attention and therefore memory towards documented Black victims of police violence in the U.S. (Wu et al., 2023). Other have found Wikipedia to be a place where editors collaborated intensively on pages relating to the Black Lives Matter movement to document contemporary events, migrate to cover new events as they happen, and dynamically re-appraise past events (Twyman et al., 2017).

Though quantitative studies researching Wikipedia are abundant, ranging from big-data analyses of citation patterns to measurements of Wikipedia's page views, they cannot identify Wikipedia's distortions, juxtapose article content with scholarship, or evaluate intentionality. Qualitative analyses, on the other hand, tend to allow more in-depth examinations of the digital practices of memory and the interactive processes that constitute memory, along with critical examinations of the biases that these can produce (Ford et al., 2023; Grabowski & Klein, 2023). Qualitative analyses typically lack the scale necessary to capture digital dynamics at a greater scale, however - especially transnational scales.

Where this study seeks to complement existing work, then, is to offer a close qualitative reading with an explicit transnational scope to triangulate through multiple digital datasets and platforms the processes and outcomes of #MeToo's digital memory footprint.

To examine these processes, this study adopts Burkey's (2020) conceptual and methodological framework to examine the three processes of memory production. First, this framework emphasises the multimodal nature of memory practices, encompassing both multitude of ways users can create, interact, and participate in social remembering, but also the multitude of platforms and devices these multimodal practices occur. This conceptual framework contends that the way users choose and interact with digital platforms and social media in relation to memory defines what they wish to remember and how they want to remember it. At core, this is a practice of *privileging* certain narratives, platforms, content types, and people. Moreover, this privileging occurs across all of curation, circulation, and claiming mentioned above. Second, Burkey's framework foreground the understanding of *who* is producing the memories, and additionally who those memories are shared with. Finally, the framework highlights the utility of metadata in understanding digital memory practices.

5.3 Research Questions

The central research question is: **How has on #MeToo lasted through digital memory?**

This central question is broken answered by tackling three sub-questions:

- How has #MeToo lasted through curation of digital memories?
- How has #MeToo lasted through circulation of digital memories?
- How have claims about #MeToo been made and contested in digital memories?

All of the foregoing questions will be answered with an explicit focus on the international scope of #MeToo, making cross-national and cross-lingual comparisons where possible.

5.4 Data

As mentioned above, there were five datasets used to address the research questions in this study. This section describes the data used in this study, from why each data set was used, to the data collection and data cleaning processes. All data was captured in the months between September and December 2023.

5.4.1 Archive: Harvard Schlesinger Library #MeToo Project

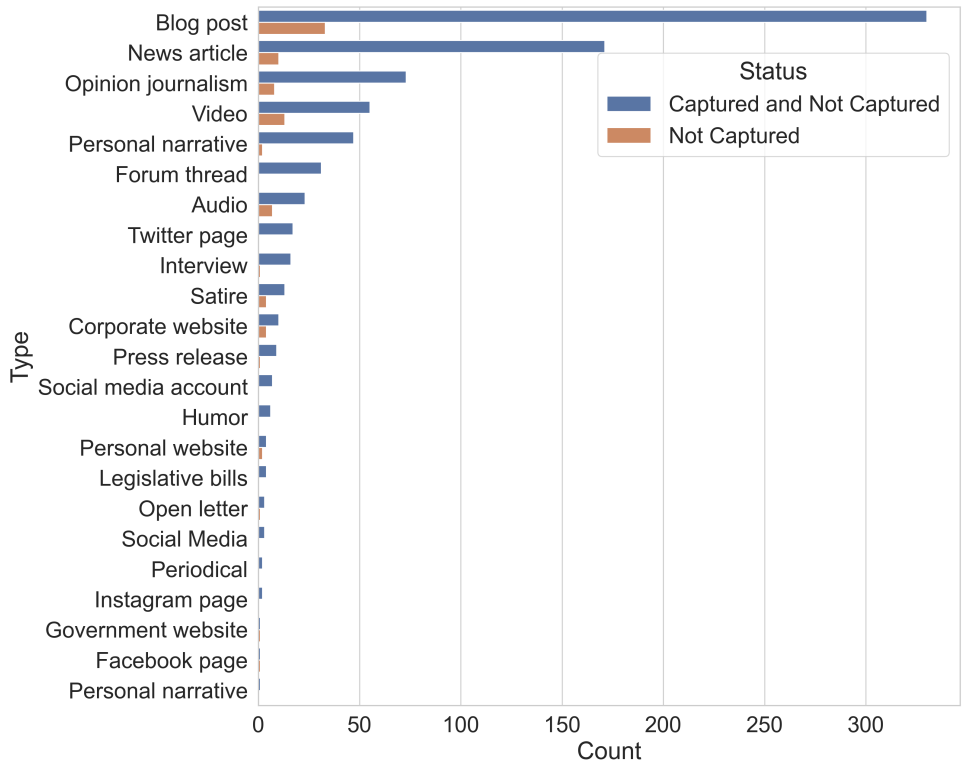
To address the first research question on curation of #MeToo digital memories, two curated Internet Archive collections were employed: the Harvard Schlesinger Library #MeToo Project (henceforth the 'U.S. collection'), with an expressed focus on the U.S. context (#MeToo Project Schlesinger Library, n.d.):

> This project will document the digital footprint of the #metoo movement and the accompanying political, legal, and social battles in the United States and will collect social media, news articles, statements of denial and/or apology, Web-forum conversations, legislation, lawsuits, statistical studies, Fortune 500 companies' employment manuals, hashtags related to #metoo, and more. The material in the collection will date from 2017 with the popularization of the #metoo hashtag (originally created in 2007 by Tarana Burke) and will end when #metoo activity subsides. The collection will be made available for interdisciplinary research on #metoo.

This archive was chosen because it is a curation of digital materials beyond a single platform or digital media type, additionally with an express focus on the U.S., where the movement began. It is valuable because few institutions outside of libraries would undertake a project to document the variety of a movement's digital

Figure 5.1

Distribution of Item Types in U.S. Collection



Note. This figure shows the distribution of item types within the U.S. Collection. These categorizations were assigned by the curation team, not the author.

footprint in such a way, and further the authoritative position the association with Harvard University conveys to the project makes the entries that comprise the collection all the more demanding of attention.

As of the time of collection in December 2023, the archive consisted of 1,155 elements. The distribution of source types in the collection is shown in Figure 5.1.

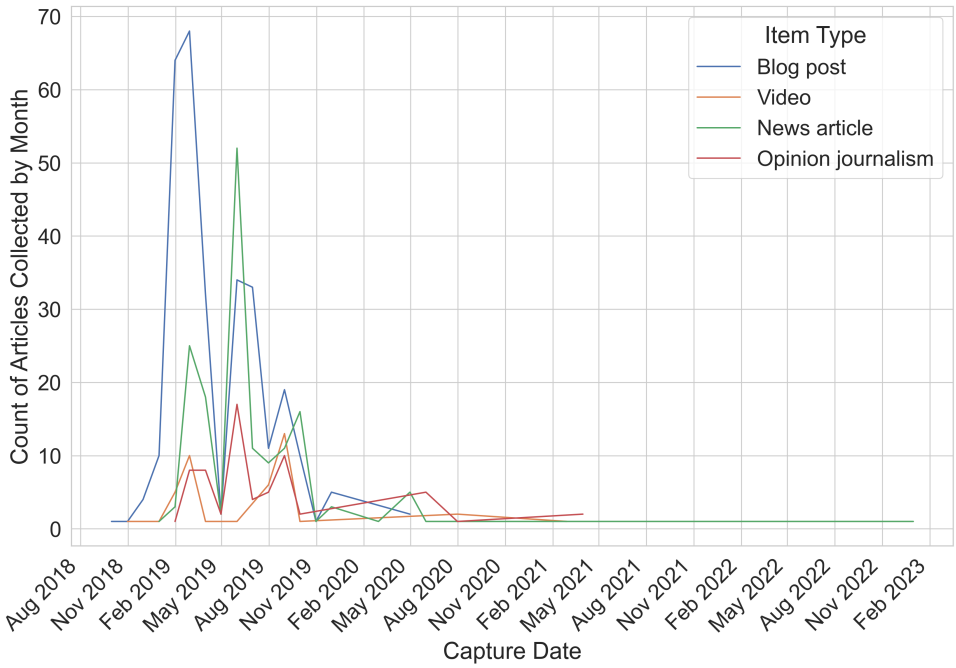
The majority (88.3%) of the data had at least one captured page in the WayBack Machine. The capture dates of the four most common item types is displayed in Figure 5.2. Fortunately, there was no one item type that suffered particularly from not having a captured version.

The distribution of collection times of the items in the collection are displayed in Figure 5.2. The vast majority of the collecting effort was conducted between November 2018 and November 2019, with blog posts being collected most frequency at first, then with more news articles in 2019. From the data, a 10% sample stratified by item type (blog post, news article, etc.) was extracted to ensure at least one item of each type would be examined. This came out to 74 items to be examined. The latest captured versions were used.

A few further observations may be made about the data. First, blog posts are by far the most common item

Figure 5.2

Distribution of Capture Dates of Items in Harvard Schlesinger #MeToo Project



type, comprising 29% (331 out of 1,155) items. The blog posts come from a diverse range of sources, the top 10 most common of which are displayed in Table 5.1.

Table 5.1

Blog Sources in the U.S. Collection

Blog Source	Count
verdict.justia.com	26
medium.com	21
www.iwf.org	18
feministing.com	13
www.aclu.org	11
www.christianpost.com	9
www.theinclusionsolution.me	8
fierce.wearemitu.com	8
www.nationalreview.com	7
www.dancemagazine.com	6

This range of sources is important to the representativeness of the collection, and that no single domain accounts for more than 10% of the blog posts collected is a positive reflection. The same is not true, however, of the distribution of news articles in the collection:

The Crimson is the student newspaper of Harvard University, and 40% (69 of 171) of news articles in the collection are accounted for by a single student publication unlikely to be as influential and widely read as, say, *The*

Table 5.2

News Sources in the U.S. Collection

News Source	Count
www.thecrimson.com	69
www.nytimes.com	11
www.thecut.com	6
www.newsmax.com	5
www.washingtonpost.com	4
hbr.org	4
www.buzzfeednews.com	3
www.bloomberg.com	3
www.teenvogue.com	3
www.indianz.com	3

New York Times, which has published much more than 11 article about the movement and associated public allegations.

Further, beyond the two most numerous item types, social media pages, and forum threads comprise a surprisingly small percentage of the collection. There exists another part of the collection that is a tweet archive, but little other social media is archived that may also have been relevant: the '#metoo' hashtag on Instagram, for example, has over 3 million uses as of late 2023, and–as will be discussed below–YouTube is also a site with many relevant digital records of the movement as a social media platform.

5.4.2 Archive: Feminist and Queer Activist Movements in Transnational China and the Asian Diaspora

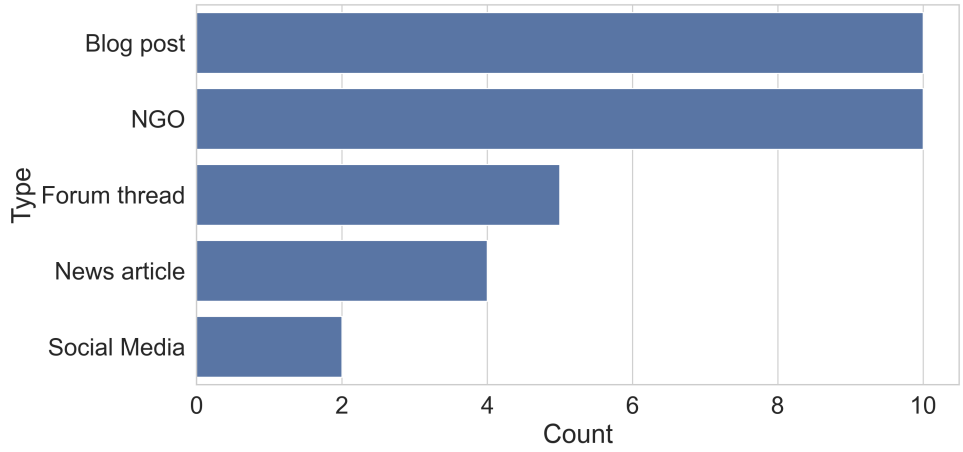
The second curated archive is the Feminist and Queer Activist Movements in Transnational China and the Asian Diaspora (henceforth referred to as the 'China collection'), compiled by the Ivy Plus Libraries Confederation. The Ivy Plus Libraries Confederation is voluntary union of 13 academic libraries across the U.S. This archive is constructed with the expressed purpose of:

> The Archive aims to systematically capture and preserve web contents related to the feminist/-women's rights/#MeToo and LGBTQ movements in transnational Chinese networks both inside and outside of China, so that scholars and students will continuously be able to access these important, and potentially ephemeral, materials.

Like the U.S. collection, it is hosted on the Internet Archive and contains captures of pages through the Wayback Machine. Immediately it is notable that the scopes of the two archives are substantially different beyond their geographical focuses: the U.S. collection explicitly identifies the #MeToo movement as the phenomenon in

Figure 5.3

Distribution of Item Types in China Collection



Note. This figure shows the distribution of item types within the China collection. Item types were coded manually by the author.

question, whereas this collection couches the #MeToo movement in China and the Asian Diaspora–therefore including Hong Kong and Taiwan–as part of the longer feminist and queer activism predating it. Originally created for #MeToo like the U.S. collection, it has been expanded to signal the importance of political context and history in which feminist movements take place.

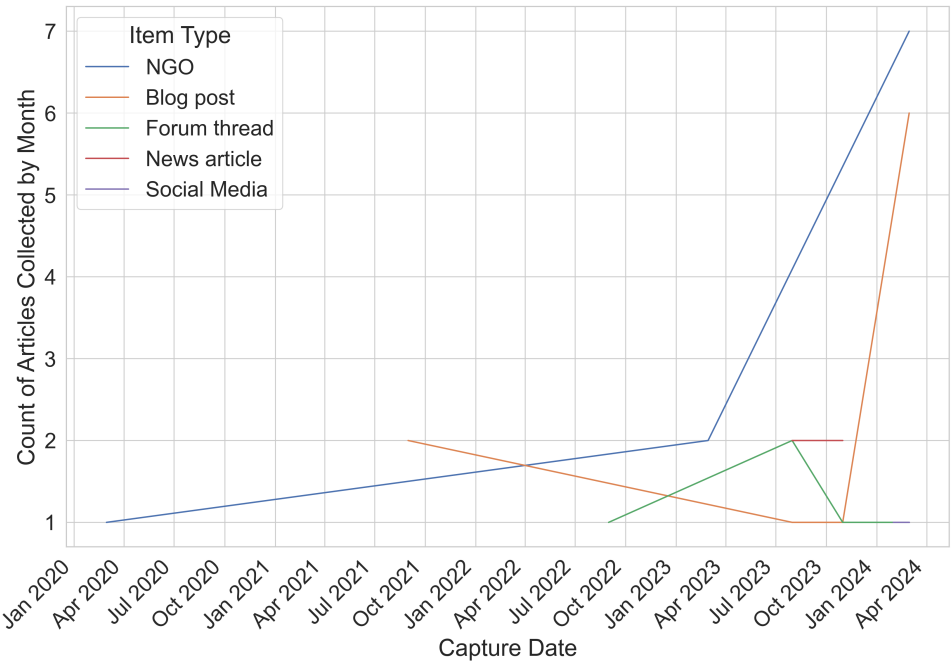
Unlike the U.S. collection described above, there were not designated categories for the items in the collection, and this China collection contains only 31 entires, orders of magnitude smaller than the U.S. collection, for a greater scope in topical coverage and population for whom these movements apply, given the size of the Chinese native and diaspora populations. The selection of each item in this collection, then, carries all the more weight with it.

The distribution of item types within this collection are displayed in Figure 5.3. Unfortunately there was no guidebook available for the coding of sites in the U.S. collection: the item types displayed were assigned by the author, attempting to match the categories present in the U.S. collection. One new item type was added: the 'NGO' item type, indicating an archival entry that is intended to preserve the digital page of a non-governmental organisation or non-profit.

The distribution of collection times is displayed in Figure 5.4. Unlike the U.S. collection, the latest capture dates of items ranged from 2020 to early 2024, even though the collection itself was started in 2016. These capture dates align better than the U.S. collection with the rest of the datasets used here, and could provide better comparisons across datasets where appropriate.

Figure 5.4

Distribution of Capture Dates for Items in China Collection



The most notable aspect of this curation is primarily the size of the archive. Upon initial inspection it becomes clear that some of the captured pages are likely intended to be entry points into a larger collection of archive worthy items. That is, for example, some NGO/non-profit captured pages were lists of blog posts on their website concerning #MeToo, but not the blog posts themselves. These blog posts one level deeper than the actual captured page are *not* captured on the Internet Archive and therefore do not strictly form part of the curation. It is possible that this was primarily a technical limitation in the creation of the dataset, as archivists may not have the requisite resources or knowledge on how to archive all pages within a domain that they might deem relevant. A similar pattern is found in the the U.S. collection above (cf. the number of *The New York Times* articles collected). However, this is a more general concern regarding digital archiving that will be revisited at the end.

Additionally, even though the archive is expressly concerned with Chinese native and diaspora populations, no archives of large Chinese websites on which #MeToo activism did appear were archived, for example Weibo (微博), a Chinese micro-blogging platform, Baidu (百度), a Chinese online encyclopedia. Only four news articles appear, none from outlets such as the *South China Morning Post* in Hong Kong. These are notable omissions, especially as Weibo has been the primary mobile media for Chinese feminists to narrate and express experiences of sexual assault and violence (Chang, 2023).

Nevertheless, ultimately these two U.S. and China collections were used to conduct this analysis because they

are both hosted on a major site of digital archives and are therefore more amenable to direct comparison, for example because they both share similar technological affordances in how pages are captured and stored. Further, both collections have an explicit geographical and cultural focus that allows insight into the variation of digital memories of #MeToo. Given there were only 31 items in total, all items were examined for analysis.

5.4.3 TikTok

To address the second research question on circulation of #MeToo digital memories, two datasets of YouTube and TikTok videos relating to #MeToo were examined. TikTok was chosen as it is an essential online platform to consider at this point in history, and therefore in relation also to any digital activism and memory work. Not only are there more than 1 billion monthly active users across the world (Bursztynsky, 2021), it is extremely popular amongst young audiences, especially amongst young women and girls (Littleton, 2021). Further, its multimodal nature combines affordances of micro-blogging Twitter, image-led Instagram, and audiovisual content of YouTube (Banet-Weiser & Maddocks, 2023).

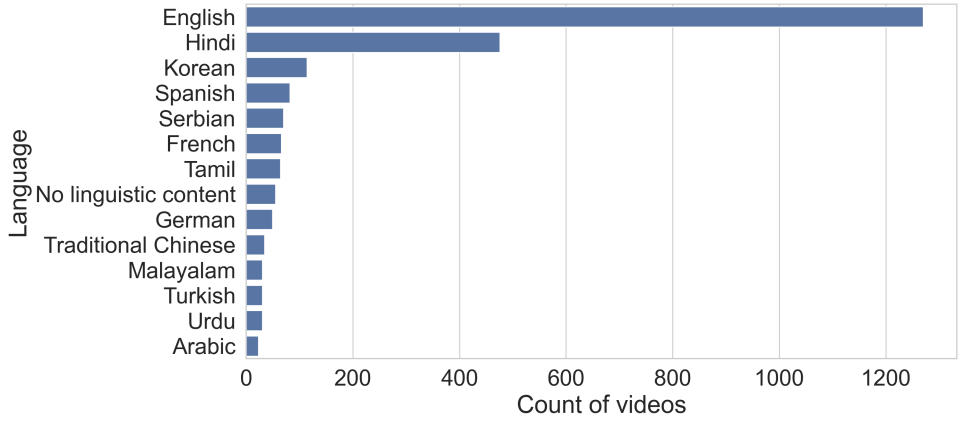
As of late 2023, no official TikTok Research API was accessible. Instead, EnsembleData's[1] unofficial API was used. Using the list of known #MeToo versions in different languages listed in Appendix B.3, separate queries were constructed, where hashtags were grouped by language (for example, #BalanceTonPorc and #MoiAussi for French). In total, for videos posted between September 23, 2023 and December 23, 2023, 5,685 video ids were collected. The video data itself was downloaded using the open source project yt-dlp[2]. Many of the results did not contain the relevant hashtags, and upon inspection of a random sample it was clear that they were not relevant and discarded. Further, a number of common hashtags and terms used in videos that were also not relevant were filtered out, for example Meghan Trainor's 'Me Too' song. 528 videos remained that contained at least one of the hashtags in the query, and were all examined in the analysis.

No further data cleaning proved fruitful due to the nature of TikTok content: descriptions are often simply lists of hashtags with a lot of noise and little signal, titles are often also non-specific or indeed carry sarcasm, and audio is often music. Users often post videos where text appearing on screen during the video communicates the actual substance of the message, but not in a consistent enough way that a structured topic model approach could be applied to the dataset.

[1] https://ensembledata.com
[2] https://github.com/yt-dlp/yt-dlp

Figure 5.5

Distribution of Audio Languages in YouTube Dataset



Note. The YouTube API v3 sometimes returned regional specification for languages, for example French (Canada, France) and English (India, U.S., etc.). Values presented in this figure are the sum total of these regional specifications.

5.4.4 YouTube

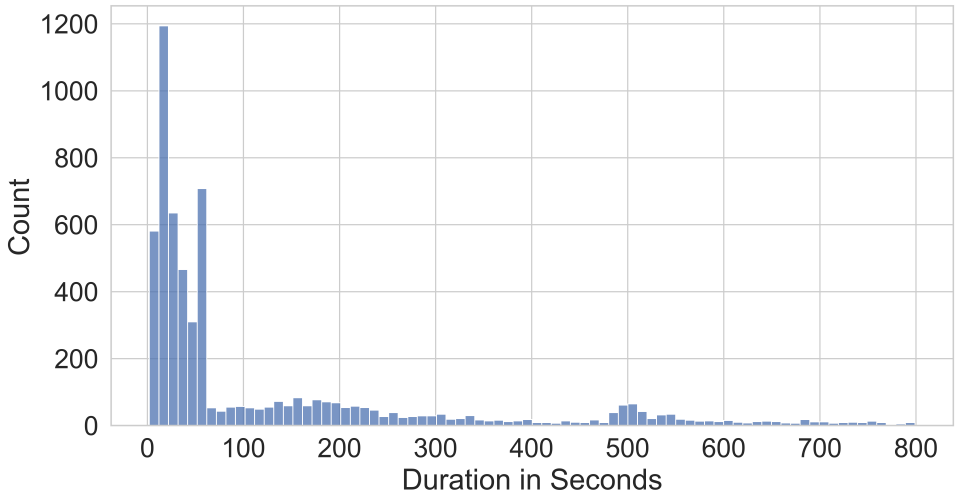
YouTube was chosen alongside TikTok because it provides a site of comparison to the content format typical on TikTok. Videos are very often substantially longer and more predictable in format, even though YouTube Shorts often inherits content from TikTok. Further, YouTube can serve similarly as a means of expression in younger generations, and has been a way to disseminate #MeToo disclosures of sexual violence (Nelon et al., 2021).

To collect YouTube data, the YouTube Data Tools (Rieder, 2015), a collection of simple tools to collect data from the platform through the official API v3, were used. As with TikTok data, queries consisting of the same set of hashtags were entered to retrieve a video list, returning 7,071 results for videos between September 23, 2023 and December 23, 2023. As of August 2023, the official API v3 no longer supported obtaining a network of recommended videos from a seed list of videos, so the results returned from the query could not be augmented through this method. As YouTube videos are often much longer and therefore larger in file size than TikTok data, audio for the data was downloaded through the same yt-dlp tool. The distribution of the audio languages of the videos is shown in Figure 5.5.

As with the TikTok data, a list of keywords were used to filter out immediately irrelevant data. Further, the returned results from the API do not differentiate between long-form, regular videos and Shorts. To ensure greater separation between this dataset and the TikTok one, videos 60 seconds and less were discarded. The 60 second threshold was determined after examining the distribution of video lengths, as shown in Figure 5.6.

Figure 5.6

Distribution of Video Duration in the YouTube Dataset



Note. Videos shorter than 60s were treated as YouTube Shorts and discarded.

To further clean the data, a BERTopic (Grootendorst, 2022) clustering was applied on the combined title, description, and audio transcription with stopwords removed beforehand in all languages where SpaCy had lists of stopwords (Honnibal et al., 2023). As the topic of #MeToo and sexual assault is a known topic within the data, zero-shot topic modeling was applied, where keywords of a topic expected in the data may be provided before the clustering occurs, allowing for greater control and clarity of the resulting output (Alcoforado et al., 2022). 1,128 videos were identified within the relevant topic. Other topics included dance videos that were not removed through the keyword filtering, regular news updates from the same few channels, gaming (Fortnite) videos, and music videos.

Of the 1,128 videos, a 10% stratified sample by language was extracted, with a minimum of 5 videos per language. A final sample of 144 videos was obtained[3].

5.4.5 Wikipedia

To address the third research question, Wikipedia articles were used. Wikipedia is one of the most frequently visited sites as of 2024. It provides content in more than 160 languages to millions of users every day, and as an encyclopedia, therefore plays and important role in knowledge production and storage. Though it is not, of course, a news site, it serves as an often authoritative secondary source of information (Lemmerich et al., 2019). Users often employ Wikipedia to further research into a subject, and to contribute towards topics on which they have expertise. It is also an important place for understanding current affairs: 30% of users visit due to

[3]N.B. more than 10% of 1,128 videos were in the final sample because of the minimum of 5 videos per language: Some languages would have otherwise returned fewer than 5 to the sample.

media coverage of a topic with Wikipedia pages (P. Singer et al., 2017). Though at first glance Wikipedia may not seem deserving of particular attention as a potentially unreliable source due to its open editing policy, its visibility and prominence make it extremely important. It is been central to defining how we understand the relationship between knowledge and digital culture (Pentzold, 2009).

By virtue of this open editing policy, of course, Wikipedia must not be understood as simply a passive, authoritative source, but an *active* producer of knowledge, noteworthiness, and historicity. Editors do the work of classifying knowledge about the world. In so doing, they necessarily participate in the delineation of what constitutes reliable knowledge on individual, groups, events, and how these link to each other, given Wikipedia's setup as a hyperlinked network of articles. What information is deserving of being encoded in an encyclopedic entry requires judgments of quality, relevance, and critically, verifiability. Verifiability is particularly important in Wikipedia's policy, which states that content should be from a 'neutral point of view', comprising 'no original research' should meet the threshold of verifiability, not truth ("Wikipedia", 2024).

There is no 'view from nowhere' or perfectly neutral point of view, as journalists well know. The assessments of quality, relevance, and reliability are inevitably to some extent a matter of perspective. Further, despite the emphasis on verifiability and not truth, Wikipedia nevertheless contains multitudes of assertive statements whose function, intended or otherwise, is precisely to establish what is true, and the truth about what a neutral, objective, reliable and verifiable statement is.

All the foregoing is demonstrative of the fact that Wikipedia editors engage in active memory work, and by virtue of it being an active producer of such knowledge and memory, it is a site of contention and struggle. 'Edit wars' amongst editors on controversial topics are well documented (Osborne et al., 2020; Sumi et al., 2011; Tsvetkova et al., 2017), though a handful of persistent, malicious editors can gain the necessary seniority to consistently produce patently false, harmful, and sometimes hateful claims as Grabowski and Klein (2023) identified amongst articles on the Holocaust in Poland where far-right Polish nationalist editors reinforced stereotypes about Jews, minimized the history of antisemitism, and more. Indeed, some scholars have even stated that Wikipedia is a 'resource to be mined, exploited, and enclosed.' (Jankowski, 2023, p.345)

Finally, though not central to the motivation of this particular study, the often authoritative space that Wikipedia occupies reinforces the need for to be examined and scrutinized as it is a key source of training material for artificial intelligence, machine learning, and knowledge graphs (Ford et al., 2023). Its 'views' have significant impacts every time a model trained on its content is asked to generate something new.

Wikipedia data was collected as follows. Using the known hashtags of #MeToo across 37 languages listed in

Appendix B.3, pages were collected through the list:search method on the Wikipedia API. This initial search retrieved 139,042 page hits. The API does not allow for more than 10,000 results to be returned for any given query to prevent overloading the API. However, it does allow for several different sorting methods of the results before the 10,000 are returned, one of which is a random ordering. Using this random ordering multiple calls with the same query were sent to the API with set time delays avoid overloading the endpoint until all 139,042 page hits were returned.

Subsequently, the following data cleaning procedure was applied. First, the search results provide snippets that matched the query on the returned pages. As Wikipedia's search engine automatically includes results from slightly modified versions of the query to be more forgiving towards typos, for example, many results were returned simply because they included the individual words 'me', 'too', or the phrase 'me too' where the page was not relevant to #MeToo. Further, many results also contained '#MeToo' or one of the non-English versions in titles of sources cited in the References section, and where the hashtags were never present in the main text. After filtering out both types of pages, 2,675 pages were left. Thereafter, to filter out pages that were still not a relevant topical fit, a topic clustering method on the matched snippets were applied using BERTopic (Grootendorst, 2022). The same zero-shot modeling as in the YouTube Dataset was used. Of the 2,675 items, 1,277 were in the relevant topic. Snippets instead of full page texts were used for topic modeling because those are the relevant parts of text within the whole text of a page, especially if there is a particularly long article about an individual where the movement is mentioned in one particular section. Some remaining pages had multiple matching snippets (a page containing multiple mentions of #MeToo): accounting for these 53 duplicate articles were removed, leaving 1,224 articles. Then, on the page titles named entity recognition was performed to separate pages about individuals from other pages. 634 pages had names in titles, 590 did not. Of the named pages, 10 individuals were sampled, and 10 non-individual pages were sampled. For these pages, the English, German, French, Polish, Japanese, Chinese, and any native versions of the pages were downloaded. Additionally, a few core relevant pages were extracted for analysis. the main #MeToo movement: the main #MeToo movement page and the four pages on the #MeToo movement in specific countries: South Korea, Pakistan, India, and China. These were examined in all the language versions available. For all pages, analysis was conducted in English and Chinese, with page versions in other languages translated via Google Translate. 10% of the pages without names was sampled, and in addition to the relevant pages mentioned, a total of 135 Wikipedia versions of pages were examined.

5.5 Methods

After collecting the datasets described above, I conducted a discourse analysis (Foucault, 1972), combining the key idea of privilege discussed in the theoretical framework above with constant inspection of the data. Discourse analysis contains much of the interpretive machinery appropriate to approach the research questions. Discourse, understood as begin a group of statements which structure the way a thing, event, or a *movement* is thought about, and also the way we act on the basis of that thinking, was the framing adopted towards the data in question. Importantly, that a *group* of statements and not individual statements is examined also entails an understanding of intertextuality: that is, that the way meanings are carried by any one discursive component depend not only on that component itself but also on the meanings carried by other components. This interdependence is the connective tissue that produces an emergent whole more than just the sum of separate statements, and is the *discursive formation*: the 'systems of dispersion' that consist of the parts of discourse and their internal relationships (Foucault, 1972, p.37).

Visuality may be a sort of discourse too (Rose, 2001), where 'visuality' indicates more than audiovisual content of YouTube and TikTok, say. Visuality is the arrangement of discursive statements and components that renders certain things visible in particular ways, and other things unseen or *unseeable* for example. Visuality as a concept in discourse analysis therefore ties closely with the notion of privileged stories and narratives in collective memory.

Discourse may be articulated in a large number of ways, most clearly here varying by the *affordances* (Davis & Chouinard, 2016) of each platform that give rise to variety in format, practices, and properties of discursive expression. This methodology understands this variety in addition to intertextuality of items within a given platform: that is, intertextuality may exist across items in the U.S. collection, but the totality of discourse must also contemplate discourse and associated intertextuality within Wikipedia.

Lastly, this methodology was also applied because of its concern with not only the organization and social production of visual, spoken, and written materials, but also to the social context and institutions through which discourses are articulated (Rose, 2001). In attending to these dimensions, discourse analysis concerns itself with the intertwining of power and produced regimes of truth. All of the above are directly relevant to assessing what is privileged (Burkey, 2020).

Therefore, these datasets were examined as sites of memory production, taking into account the platform affordances that shape the modes of production and representation on each platform (Davis & Chouinard, 2016), the composition of the elements of the datasets, and finally the social intentions and impacts of the produc-

tions behind each dataset. For the curated datasets, the technological affordances of the Internet Archive, the selection policies of the curation teams, and the temporal coverage are examined. For the circulation datasets of TikTok and YouTube, the platform affordances of audiovisual content, the themes and types of narratives and audiovisual content composing the datasets, and the resulting social role these play are examined. Finally, for the Wikipedia entries, the nature of the Wikipedia editing and editing policy, the composition and structure of articles, and the subsequent impact of those claims made are assessed.

Critically, all the above was assessed, where possible, across languages and countries, seeking to understand differences in these productions and representations of memory of a 'global' feminist movement.

5.5.1 Procedure

The annotation process proceeded as follows with myself as the sole coder. Coding was undertaken using MaxQDA software. I followed Bryman's (2012, p.581) coding procedure, which began with an initial reading of all the data by platform, and upon the second reading making notes about significant remarks or observations, revising, combining, or discarding codes appropriate. Initial notes were made with reference to the primary analytic themes of visibility, privilege, and the processes of production as described above (Burkey, 2020).

Further, each type of dataset also demanded platform-specific questions given the differing sets of affordances. Some of the questions I posed for each type are the following. For the curated datasets, questions, I attempted to identify elements or properties relating to an item in the collection that prompted the curator to choose it: whether it was a particular part of the content, the publisher of the content, the platform the item was hosted on, the timing of publication of the item, or something else. For Wikipedia, what sections are consistent between language versions? Which pages exist and don't exist, and why might that be? How many language versions exist for certain pages, and what explains the variation between the number of language versions between pages? For TikTok and YouTube, what are the creators trying to communicate, and to whom? How does the creator understand their contribution in relation to other content and events, especially when their content is in reply to another piece of content or in reaction to recent events? What are the methods they use to communicate that message? How are creators using either or both visual and audio components - for example, through static on-screen text, only audio and static image, or something in between? Why? Throughout all the above, unexpected or emergent themes were noted along the way for review in the second pass.

In the second pass, the data from each major theme was re-examined and re-analyzed to consolidate themes and reconsider coding results. Codes were grouped where they were similar, such as the criticism of #MeToo in its

various forms including perpetuation of rape myths, an entanglement of the movement with other gender frustrations, etc. These revisions in the second pass were conducted with close attention paid to: critically assessing why certain language was used; the producers of the discourse, with careful attention paid to what was included/excluded. Attention was also paid to anything that was emphasized in the discourse and the intertextuality of any piece data in relation to the others in its major theme, including what direct and indirect speech has been included.

From the set of codes after the second reading, the most salient codes are reported here: codes that reveal the most about–whether by being most unexpected or by being an important part of–how the processes of collective memory are constructed. Salience was chosen over frequency or most common codes, as frequency is subject more to particularities of sampling.

5.6 Results

5.6.1 Curation

5.6.1.1 U.S. Collection

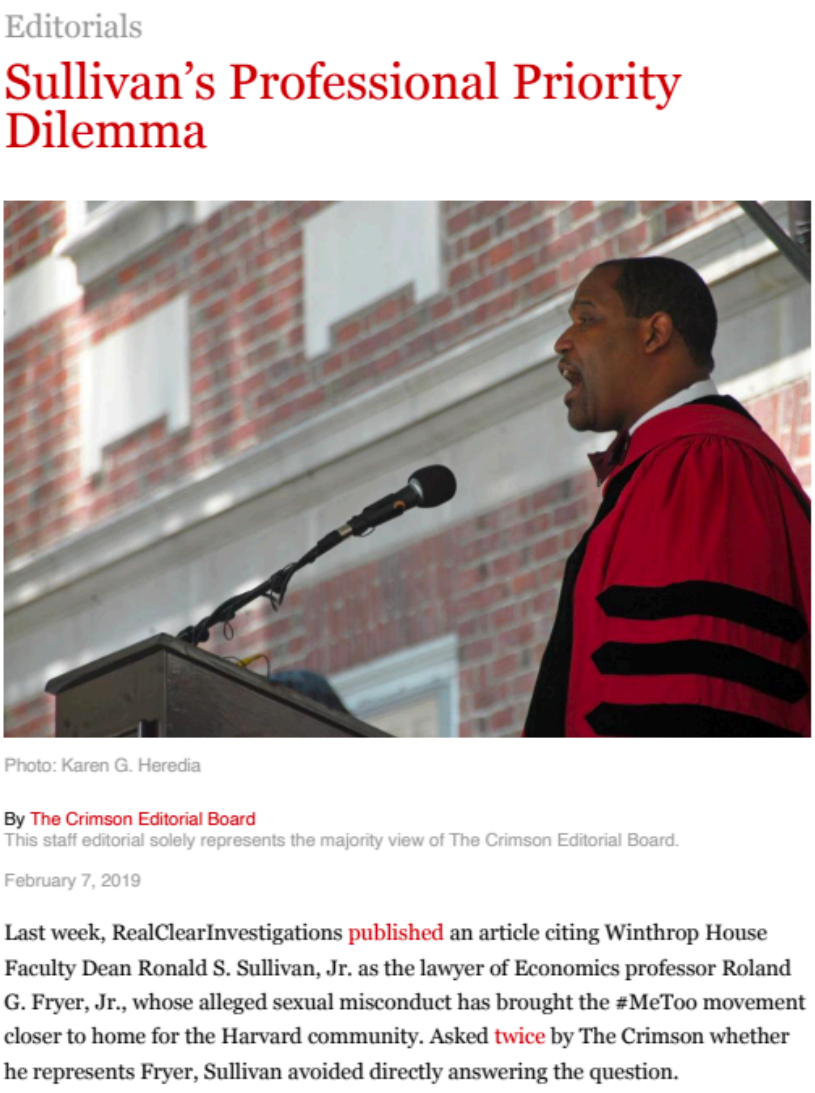
The U.S. collection within represents a noteworthy aggregation of digital materials, providing a centralized repository to content not readily available elsewhere. However, this collection exhibits significant limitations that constrain its utility for comprehensive research. These limitations encompass its selection policy, technological capabilities for archiving, and the temporal range of the content it encompasses. Ultimately, these factors mean the collection privileges narratives and voices already with visibility and platforms, especially ones that are from or are a part of news or advocacy organizations.

In terms of selection policy, one notable aspect mentioned above is the disproportionate number of articles originating from the Harvard Crimson, such as the one in Figure 5.7. This is likely due to the collection being administered and created by the Harvard Schlesinger Library. Nevertheless, in so skewing the distribution of news articles collected, the archive may unintentionally convey the impression to future visitors to the archive that Harvard's #MeToo cases are more central to understanding the movement's history than they really are. Immediately, we can observe a privileging of not just events that occur at this particular institution over other institutions, but that harassment cases at higher education institutions deserve special attention. Worse, this collection has not comprehensively covered even #MeToo at Harvard specifically: there have been survivors speaking out about harassment at Harvard not included in the collection (Schwarz, 2023).

Beyond the disproportionate inclusivity of the Crimson, other notable omissions occur. For example, the web-

Figure 5.7

Example Article from Harvard Crimson in U.S. Collection



Editorials

Sullivan's Professional Priority Dilemma

Photo: Karen G. Heredia

By The Crimson Editorial Board
This staff editorial solely represents the majority view of The Crimson Editorial Board.

February 7, 2019

Last week, RealClearInvestigations published an article citing Winthrop House Faculty Dean Ronald S. Sullivan, Jr. as the lawyer of Economics professor Roland G. Fryer, Jr., whose alleged sexual misconduct has brought the #MeToo movement closer to home for the Harvard community. Asked twice by The Crimson whether he represents Fryer, Sullivan avoided directly answering the question.

Note. This figure shows an example article from *The Crimson*, a Harvard University publication, in the U.S. Collection. Articles from the *The Crimson* accounted for a disproportionately large part of the news articles archived.

site of the Me Too movement[4] led by founder Tarana Burke has no entries in the collection though they have published a number of blog posts discussing #MeToo. Many news sites also missing or underrepresented in how important they both in spreading awareness of #MeToo in the U.S. during this time period, publishing opinion pieces, and resulting chronicling legal trials. Legal proceedings and legislative documents are also unfortunately incomplete, in an area that would potentially have been the most straightforward to achieve equitable coverage: the collection contains four bills, three of which were read in the House of Representatives, and one in the Pennsylvania General Assembly. Other bills were being proposed, debated, and passed during this time, for example a few equal rights advocacy bills were signed into law in California that were known as '#MeToo Bills' (Eagle, 2019). The resulting selection of materials in the collection therefore displays an approach that cannot be called comprehensive of digital materials around #MeToo in the U.S, and does foreground and privilege sources with greater pre-existing visibility and prestige.

Similar trends were apparent with the yet more item types: though stated as a part of their collection goal, the U.S. collection had no employee manuals, and more broadly had very little coverage of workplace policies and employment practices, though public discussion of #MeToo often centers around harassment and assault occurring at work. One news report about Uber dropping the requirement for employees and drivers to resolve disputes about sexual harassment and assault through arbitration before court was included, but notably this was not a primary source from Uber. What is lost is the ability to appraise what responses have been across of range of industries, but also shifts the emphasis of the discourse onto those more well-documented and substantive portions of the collection.

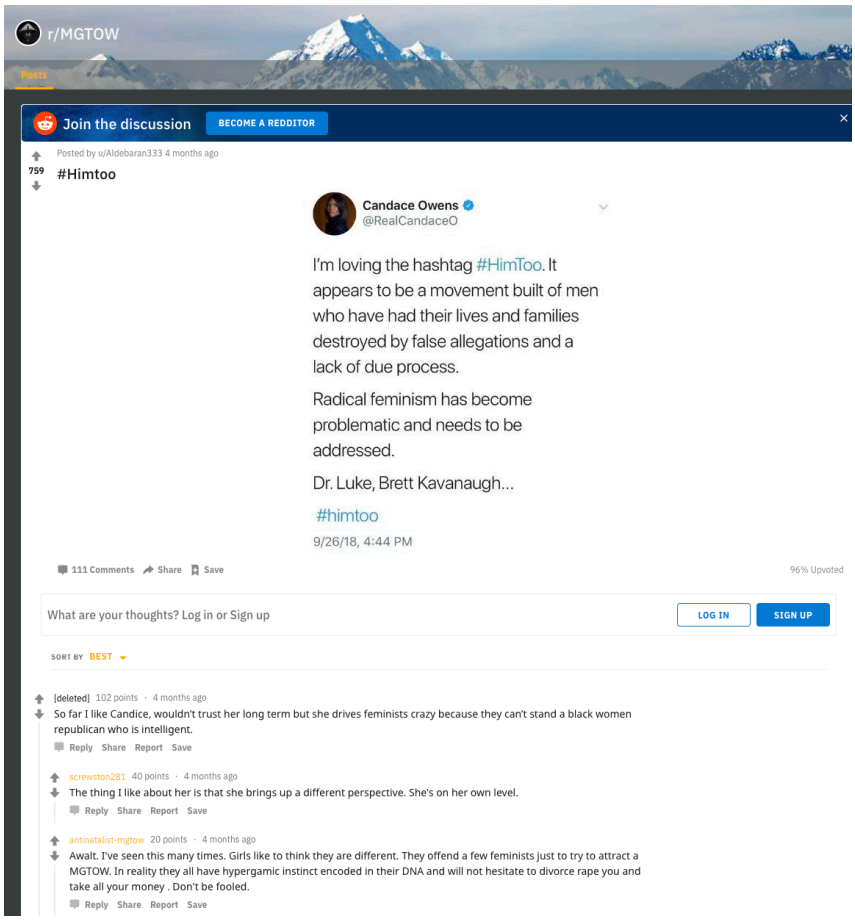
However, the selection policy's intention to be more representative shines through in some of the personal narratives and blog posts from individuals does make strides to including more individual narratives and opinions–both supportive and in criticism of–the movement. For example, the collection features individual blog posts about their #MeToo journey as well as Reddit threads. The latter is shown in Figure 5.8, though again it is unclear why this post was chosen from the r/MGTOW (Men Going Their Own Way) subreddit as opposed to others that may have received large numbers of upvotes.

Reddit posts like Figure 5.8 additionally demonstrate some of the apparent technological capabilities of either Internet Archive in preserving digital content also present challenges, particularly with the archiving of social media account pages and forum threads. Part of the collection is a separate Twitter archive collected through the Twitter API, allowing for much more robust access and analysis for any future analysis. This suggests, however, that Reddit and social media might–and perhaps *should*–be archived in a similar way. The way it is currently

[4] https://metoomvmt.org/

Figure 5.8

Example Archived Reddit Thread



Note. This figure shows an example Reddit article archived in the U.S. Collection. Unlike Twitter data, Reddit pages archived were not collected in a systematic manner or in a format readily usable for further analysis in future.

archived may be the result of a limitation in expertise and/or technical capability, however, a common challenge to archivists.

Finally, the collection's temporal coverage is narrowly confined to the years between 2018 and 2019, a limitation that excludes significant events and movements that extend beyond this period. For instance, discussions surrounding the Depp v. Heard trial in 2023, which are often mentioned in the same breath as the #MeToo movement, and even considered an evaluation or a judgment *on* the movement, are absent. Years on, as will become apparent in the following analysis of the other datasets, memory-making and contestation about the legacy of #MeToo very much constitutes digital records that would belong in this archive. Many news articles, for example, have concerned themselves with thinking and opinion structured by such ideas as life 'the era of #MeToo' or 'post-#MeToo'. The temporal coverage of the collection, then, privileges unduly the earlier digital traces of #MeToo in the U.S., possibly more reactionary and with less recorded, for example, about how the movement's influence globally has potentially reflected back into the U.S. context.

5.6.1.2 China Collection

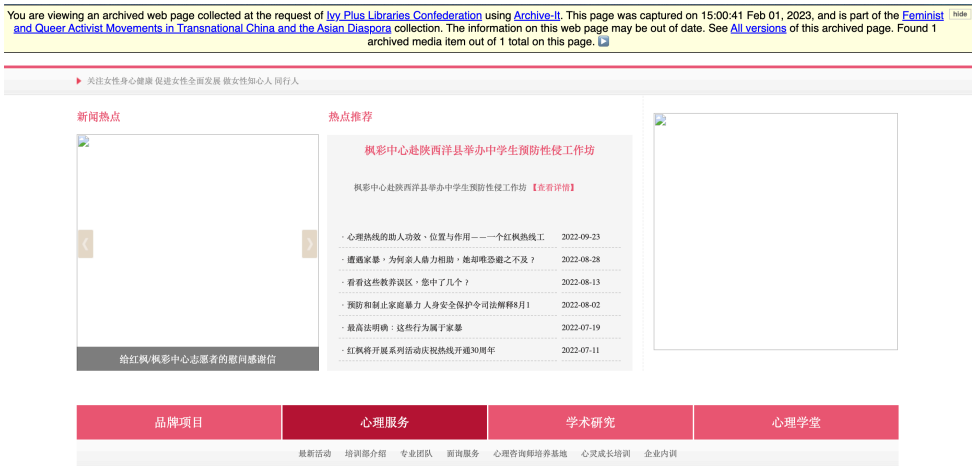
The China collection suffers more acutely from representation problem of the U.S. collection. With only 31 entries with a professed scope even larger than that of the U.S. collection by covering transgender and queer activism, what each entry says about the collection's selection policy is that much greater.

Immediately noticeable amongst the entries is the lack of specific pages on websites. Many archived pages were the homepage of either blogging or NGO/non-profit sites. One example is shown in Figure 5.9. Even though it is apparent what the organization is and stands for, and has links to individual blog posts or news updates such as the second one displayed: 「遭遇家暴，为何亲人鼎力相助，她却唯恐避之不及?」, meaning 'Upon suffering domestic violence, why was she so keen on avoiding help from her family?' A more thorough documentation of such articles would have greatly improved the visibility and power afforded to these authors and organizations. These pages were all belonging to organizations with feminist activism in their core mission, and whilst the work these organizations perform are extremely important, the current capture method tragically fails to preserve much of their work. This is especially true given the example Red Maple (红枫) shown in Figure 5.9 is no longer accessible outside of the Internet Archive.

Accessibility and, in general, censorship, is a key differentiator between activism in the U.S. and China (Liu, 2023; Zeng, 2020). Archives of activist records, therefore, all the more important in not only constructing collective memory of activist efforts, but to ensure that they are preserved at all. For example, Dr. Luo Xixi (@cici 小居士, @ciciXiaoJuShi) posted a signed letter on Weibo accusing Beihang University professor Chen

Figure 5.9

Example Archived Homepage of an Advocacy Organization Red Maple (红枫)



Note. Example archived homepage of an advocacy organization in the China collection. By the way the Wayback Machine archives pages, no links on the homepage and therefore no actual text of blog posts or information deeper in the site was visible.

Xiaowu of sexually harassing her and other graduate students while she was a doctoral student. This was the post that went viral and helped spark the #MeToo movement in China, but no Weibo posts archived in the collection.

Some awareness and intentionality of such preservation, however, was present. it contained one entry highlighted different methods activists have used to do memory work: the use of a GitHub repository. GitHub is a code hosting platform for software developers' collaboration and version control, and ostensibly has little to do with the construction of maintenance of collective memory. It has, however, in the case displayed in Figure 5.10, been co-opted as a place to record queer activism in China: where files of code would usually be entered, this repository has instead been used as a folder of historical timelines of a number of individual cases of queer activism. Each markdown document (delineated by the '.md' extension) contains a summary section followed by sections on background context, legal process timeline, and links to news coverage. The choice to include such a repository in the Internet Archive collection lends legitimacy and visibility to this archival practice on GitHub.

Overall, the China collection remains further incomplete than the U.S. collection. Rather than direct archival practice, the selection policy reflects archiving locations and repositories of activism or sites of archives in their own right. As such, the collection is perhaps better understood as a signposting directory rather than an *archive*.

Figure 5.10

GitHub Repository Archiving Queer Acts in China



Note. This figure shows the GitHub repository archiving queer acts and feminist activism in China, utilizing the built-in version control and public-facing archival nature of GitHub to re-purpose towards activist memory rather than for computer code.

5.6.2 Circulation

5.6.2.1 TikTok

The TikTok sample comprised videos concerning #MeToo in the following countries: Taiwan, Colombia, Spain, Argentina, South Korea, the UK, France, and Italy. Of these, French TikTok videos were by far the most common. It is first noteworthy that videos with subject ties to #MeToo are prevalent in late 2023. Especially on the TikTok platform, where trends fade in and out of fashion with great rapidity and regularity, the fact that #MeToo remains a consistent topic indicates at the very least that the movement remains *in* memory, and simultaneously that memory work about #MeToo is being actively constructed.

What follows are the themes observed amongst these videos.

Rape Myths and Backlash

Rape myths are false statements about sexual assault or violence that are pervasive and reinforce social stigma and prejudice against survivors (Burt, 1991; Franiuk, Seefelt, Cepress, & Vandello, 2008; Kitzinger, 2004). As has been shown in Article II, the advent of #MeToo has not unraveled the prevalence of rape myths, far from it. A major theme of videos across all countries was the dispelling of a range of such rape myths, and moreover relating them to the #MeToo movement. In doing so, these creators achieve multiple ends: contravening the rape myth(s) in question that they are targeting in the video, and reinforcing a message of the movement.

The association of the contravention of a rape myth and the movement appeared in a number of ways. Some creators explicitly invoked #MeToo as a common starting point to launch into the discussion of the specific rape myth, such as one Taiwanese creator, who is correcting common myths and narratives about when survivors come forward to report an assault:

> 最近打開電視，都是在說「米兔」啦。有些人就在說：「奇怪捏，那些受害者當時怎麼不報警、不說出來呢？」你有沒有想過，事情發生的當下是非常突然的？最好有人會說：「小姐，我現在要來性騷擾喔。」最好的有啦。受害者那時候是非常害怕的，不知如何是好。那些受害者要跳出來要說這些事情，要拿出多大的勇氣？
>
> [These days we often hear "#MeToo" on television. Some people are saying: "It's strange, why didn't those victims call the police or speak out?" Have you ever thought about how sudden everything is in the moment? Wouldn't it be ideal if the perpetrator announces:"Miss, I am going to sexually harass you now." That would be best. Survivors are terrified at the time of assault and don't know what to do. How much courage does it take for those victims to come forward and

say these things?]

Some creators from the U.K. rejected some common backlash against the movement, claiming the movement has 'gone too far', or otherwise that feminism has done so:

> And these are the men that are trying to change the narrative of the Me Too movement. And they're doing it in a very, very intelligent way. They're doing it via deflection. They're bringing up things that are important, but not necessary to what the discussion is about. They'll say things like, "What about men? Men get sexually assaulted too." Yes, yes, they do, by men. 84% of male sexual assault survivors were sexually assaulted by men. "Well, what about all the false allegations?" Well, less than 1% of rape allegations are false. "Well, it's a witch hunt. It's a bloody witch hunt." Well, it's not. Mainly because witches didn't exist. That's why witch hunts were shitty. Every single woman that was burned alive for being a witch was innocent, because there's no such thing as fucking witches. There are such things as rapists.

Other French creators contravened myths about Black women being hypersexualized:

> Cette année, je m'en suis jamais rendue autant compte que si une femme noire, d'autant plus racisée en général, mais d'autant plus noire,. s'il t'arrive de disparaître ou que tu sois en danger, ça va moins être pris en compte, moins pris au sérieux.. Pourquoi ? Probablement parce que les femmes noires sont fortes.. Attention, je dis pas que les femmes noires ne sont pas fortes.. En général, les femmes peuvent être fortes, que ce soit de caractère, de ceci, de cela.. Mais là, ce n'est pas le sujet.. Puisque vous êtes bien assez fortes, on peut vous traiter comme tout, sauf la bonne victime.
> [This year, I've never realized it as much as if a black woman, all the more racialized in general, but all the more black ,. if you happen to disappear or are in danger, it will be less taken into account, less seriously.. Why? Probably because black women are strong.. Be careful, I'm not saying that black women aren't strong.. In general, women can be strong, whether in character, in this, in that.. But there, that's not the point.. Since you are strong enough, we can treat you like anything, except the good victim.]

In this way, #MeToo is incorporated into contemporary memory through its continued association with the striking down of rape myths, and of the courage the speak out to debunk narratives. These debunking practices were strongest amongst French, and Taiwanese creators.

Figure 5.11

Example of French TikTok User's Disclosure



Note. This figure shows an example of French TikTok user's disclosure of sexual violence with the floating text "We were friends, and yet you dared to manipulated and rape me" and background music. The image is truncated to remove identifiability.

Disclosures of Personal Experiences of Sexual Assault

Another strong theme amongst the videos across the countries was the active disclosure of personal sexual assault. French and Spanish creators were particularly active in this arena, Neither South Korea nor Taiwanese creators had such videos present in the sample.

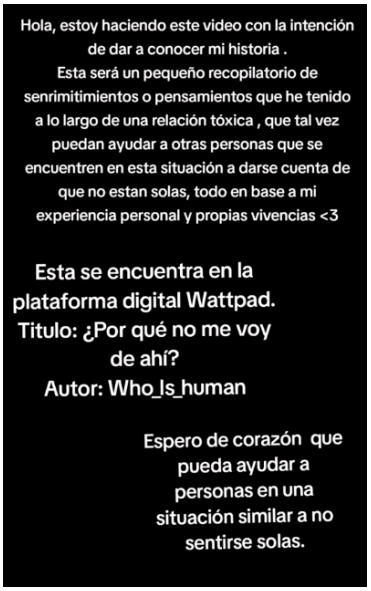
The affordances of TikTok allow for a richer, more nuanced, and more varied way of disclosing. This manifested in a number of ways: some users preferred to overlay floating text onto a background video of themselves, as in Figure 5.11, and some preferred no music and to speak directly into the camera. Others creatively used the lyrics of the song playing in the background to highlight a point they were making, indicating through visual gesture what particular line or word they wanted to emphasize. Still others preferred to have a series of still images in a fashion closer to Instagram posts with only light text on a dark background, with no audio or other visual content, as in Figure 5.12.

These new nuances and options in disclosure represent a marked difference from the beginning of the movement on Twitter. As a micro-blogging platform, Twitter restricted equivalent posts to text and occasional screenshots of text for extra context. The audiovisual, often bite-size in length, format of TikTok affords users still a text-only approach as in Figure 5.12, but also more visually rich approaches.

These disclosures participate in the formation of memories of #MeToo insofar as they continue the core message of 'me as well' in public declarations of survivor-hood.

Figure 5.12

Example of Spanish TikTok User's Disclosure



Note. This figure shows an example of Spanish TikTok user's disclosure of sexual violence with the floating text "'Hello, I am making this video with the intention of making my story known..." and background music.

Calls to Action

Content in Spanish, especially originating from Latin America, was much more centered around traditional social movement calls to action. Figure 5.13 shows such an example, where the movement hashtag #NiUnaMenos was used in conjunction with a case-specific hashtag #JusticiaparaAndrea to call users to join an upcoming meeting.

Other examples included calls to speak out more generally, or to attend a public demonstration. These examples illustrate how the activists see the utility of invocation of #MeToo. More broadly, this foregrounding of calls to (offline) organization and political contention speaks to the the complexities that characterize feminist activism in Latin America. Recently, feminist movement in the region have called to move beyond identity politics and positioning of women as a minority group; rather, strides have been made to connect feminist challenges to the status quo with groups not historically aligned with feminist politics, such as trade unions, leftist parties, indigenous associations, and more (de Souza & Rodrigues Selis, 2022).

These moves are an outgrowth of a few factors. First, women face severe violence and oppression in Latin America, so much so that the United Nations (UN) classified Latin America and the Caribbean as the world's most violent region for women (Essayag, 2017). Brazil, for example, saw steadily rising homicides of women across the country from 1980 all the way to 2013 (Waiselfisz, 2015). Second, the disjunction between apparent

Figure 5.13

Example of Calls to Action



Note. This figure shows an example call to action found commonly amongst the Latin American TikTok sample.

Figure 5.14

Example of Chronicling #MeToo History in South Korea on TikTok



Note. This figure shows the beginning of an example TikTok from a South Korean creator chronicling the history of #MeToo in the country. The text translates to: "South Korea's MeToo movement. The most recent events in Korea..."

legal protections against gendered (including sexual) violence and that unyielding rise in rates of violence against women is particularly striking and pushes more and more articulations of feminist anger. Third, an enduring legacy of coloniality normalizes violence against women's bodies as an expression of masculine community and power, especially over marginalized groups (de Souza & Rodrigues Selis, 2022). This has been called a war on the bodies of women (Segato, 2014). All of the above is consistent with the increased urgency, collective organizing, and policy-focused targets of the #MeToo TikTok content observed in the data, in contrast with the more personalized, *connective action* nature of what was seen from other countries.

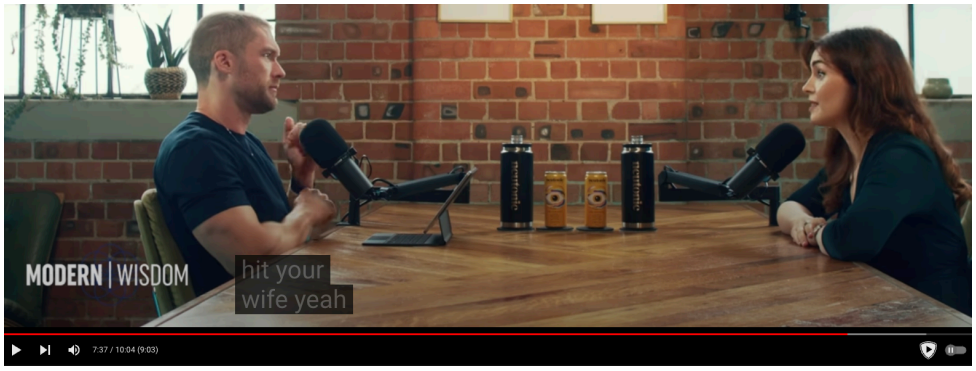
Chronicling #MeToo

Some creators, in actively recalling #MeToo, contributed to constructing and reinforcing collective memory of the movement by chronicling events, such as in Figure 5.14, a narrated series of text displays chronicling a recent prominent case in South Korea concerning an actor Oh Young-Su (오영수).

Overall, collective memory of #MeToo is actively being built and utilized on TikTok in various ways. Notably, there was comparatively very little content on TikTok with the #MeToo hashtags that were purely backlash against the movement, far-right content, or men's rights activists. This was markedly different from the YouTube content, to which we now turn.

Figure 5.15

Example of Podcast Type Movement Backlash



Note. This figure shows an example podcast recording on YouTube.

5.6.2.2 YouTube

YouTube videos, by dint of being much longer than TikTok videos, lend themselves to longer commentary-type videos. Also different was the distribution of countries of origin and subject for YouTube videos: Canada, Spain, Taiwan, Mexico, France, Argentina, U.K., India, Turkey, Germany, and the U.S. were the countries in the YouTube sample. Unlike TikTok, two dominant themes of videos presented themselves.

Movement Backlash and Perpetuation of Rape Myths

A significant proportion of the videos examined exhibited vitriol and backlash against the #MeToo movement regardless of country or political context. Some of these are videos of podcast recordings, partially explaining the much greater prevalence of videos critically attacking the movement and often perpetuating myths and falsehoods about sexual assault, survivors, and how men should react or comport themselves in reaction to it. These video types were much more prevalent in the U.S. and U.K. than other countries. Oftentimes these videos would include a woman to provide an air of authenticity or authority on the subject of feminism but nevertheless provide shallow and harmful opinions about how feminism has 'gone too far'. Figure 5.15 shows an example of this from the *Modern Wisdom* show, where #MeToo is understood as first and foremost attacking men, and as a movement that wishes to apply a blanked policy to all men.

Other times, videos featured talk panels of ostensibly #MeToo supportive speakers, but with a heavy assumption that #MeToo's key message and learnings are things that survivors can and should to better. Figure 5.16 displays the headline of a talk panel in Taiwan that exemplified this theme. The text in the Figure translates to: "Special Mission 10: #MeToo continues to be a hot topic; how can we learn to say NO?" In this caption and throughout the panel, it becomes clear that the mission is simply a further onus on survivors to do better, to shield themselves

Figure 5.16

Example of Perpetuation of Myths



Note. This figure shows a thumbnail from a YouTube video of a Taiwanese talk show in late 2023. The text translates to: "Special Mission 10: #MeToo continues to be a hot topic; how can we learn to say NO?". The video consisted of a panel where panelists were invited to implicitly agree that the core problem was women not being able to better say 'no'.

from aggression better. Such memory-making of #MeToo consolidates its association with the long history of victim-blaming: what could and should the victim have done better? Said better? Or dressed differently?

Documentary

Lastly, some news outlets and media organisations have compiled documentary-like records of #MeToo. A documentary video on how #MeToo has changed industry practices in Bollywood, for example, is amongst the type of video in these documentaries. These documentaries focused often on a particular industry, typically the film and entertainment industry, and whilst some added context and impacts for survivors and those who had spoken out, mostly they concerned how the movement and reactions to it have changed practices that have made work potentially harder, or prominent men in the industry more wary of interacting with women.

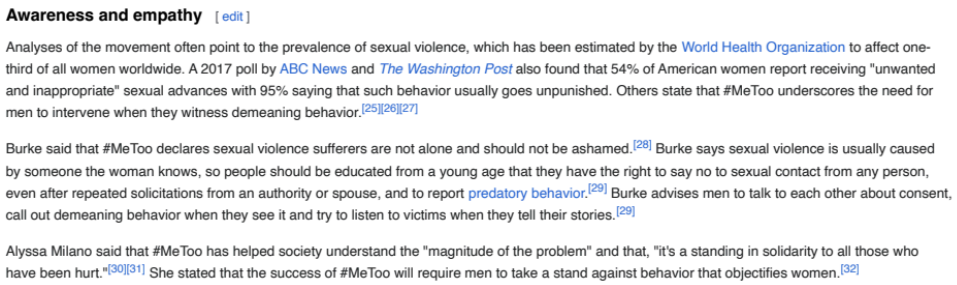
5.6.3 Claims

5.6.3.1 Wikipedia

Articles on Wikipedia exhibit a fragmented, inconsistently structured approach to recorded memory of #MeToo. Quality and depth of articles drops rapidly once leaving the English versions of pages, and which components remain in these pared down versions is revealing. It is worth noting that Wikipedia policy does not mandate language versions of any given page to closely resemble each other, or be faithful direct translations. Additionally, longer articles often acquire a list-like nature, typically listing series of public allegations associated with #MeToo. Both these facts significantly impact both the explicit and implicit claims available as part of public,

Figure 5.17

'Awareness and empathy' Subsection in English #MeToo Movement Wikipedia Page



Awareness and empathy [edit]

Analyses of the movement often point to the prevalence of sexual violence, which has been estimated by the World Health Organization to affect one-third of all women worldwide. A 2017 poll by ABC News and *The Washington Post* also found that 54% of American women report receiving "unwanted and inappropriate" sexual advances with 95% saying that such behavior usually goes unpunished. Others state that #MeToo underscores the need for men to intervene when they witness demeaning behavior.[25][26][27]

Burke said that #MeToo declares sexual violence sufferers are not alone and should not be ashamed.[28] Burke says sexual violence is usually caused by someone the woman knows, so people should be educated from a young age that they have the right to say no to sexual contact from any person, even after repeated solicitations from an authority or spouse, and to report predatory behavior.[29] Burke advises men to talk to each other about consent, call out demeaning behavior when they see it and try to listen to victims when they tell their stories.[29]

Alyssa Milano said that #MeToo has helped society understand the "magnitude of the problem" and that, "it's a standing in solidarity to all those who have been hurt."[30][31] She stated that the success of #MeToo will require men to take a stand against behavior that objectifies women.[32]

Note. This figure shows the 'Awareness and empathy' subsection in the English #MeToo Wikipedia entry, a rare occurrence for amongst the different language editions of the #MeToo page.

collective memory on #MeToo.

The main #MeToo movement page in English is, as expected, by far the longest. Notably, a section on the purpose of the movement immediately occurs after the introductory section mandatory for all encyclopaedia entries. Already this is an unusual ordering, and is not true of other pages of instances of feminist activism ("SlutWalk", 2024), nor of the Black Lives Matter page ("Black Lives Matter", 2024). The subsections of this Purpose section were: 'Awareness and empathy', 'Policies and laws', 'Media coverage', 'Issues with social norms', 'Reform and implementation', and 'Role of men'. That 'Awareness and empathy' is the the first listed purpose of the movement is a non-trivial and positive statement about how the movement is remembered: visibility and consciousness raising is a core part of much feminist activism, serving both to name a problem that was previous invisible or worse unspeakable, and to reframe a problem that was only understood from a limited perspective (in #MeToo, that sexual violence has been seen from the default male perspective) (Boyle, 2019a; Serisier, 2018). Within this subsection on awareness, shown in Figure 5.17, however, no activist voices are referenced except Tarana Burke and Alyssa Milano, and otherwise only news organizations and polls are leveraged to present this purpose of the movement.

The 'Media coverage' subsection, by contrast, does not describe media coverage as a *purpose* of the movement, but rather describes instances where #MeToo and associated public allegations have received media coverage. Media coverage as a *purpose* of the movement might better be understood either in terms of the consciousness raising, or to change the way the media engages with sexual assault and survivors entirely (Hindes & Fileborn, 2019), neither of which are mentioned in this subsection.

The 'Role of men' subsection nods to the links between feminist activism and a growing crises surrounding masculinity more broadly, a theme that returns later in the articles in the 'Criticism' section. This subsection

highlights a 'level of anger and frustration' ("MeToo Movement", 2024). Nowhere before this point did the article mention deep anger and frustration experienced by the volume of survivors whose willingness to say 'me too' is the genesis of the movement itself. Rather, it is still male anger and frustration that demands attention, even in written record (Berlant, 1988).

The rest of the main #MeToo movement page includes a section on the international spread and response to the movement, in recognition of its global impact, but more significantly a long 'Criticism' section. This section features a long subsection on 'False accusations', along with 'Undefined purpose', 'Overcorrection', 'Possible trauma to victims', 'Exclusion of sex workers', 'Failure to address police misconduct', 'Lack of representation of minority women', 'Overemphasis on specific cases', and 'Disregard for incarcerated women'.

The 'False accusations' section, though stating that multiple sources indicate how rare false accusations actually are at the beginning, reveals quickly that the editors were at pains to highlights how false accusations remain a 'valid [systemic] concern'. The text goes further, diving into potential reasoning for false accusations, naming attention-seeking and revenge–commonly documented rape myths (Burt, 1980)–as key reasons the most frequent reasons for false accusations. Indeed, the longest and most well cited paragraph in this subsection is one on Gary Oldman, who was exonerated from a accusation of domestic violence, going into irrelevant detail such as Oldman's attendance at the Academy Awards at the time of the legal proceedings. Outside of the 'False accusations' section, however, space is made for the underrepresented, including women of colour, sex workers, and incarcerated women.

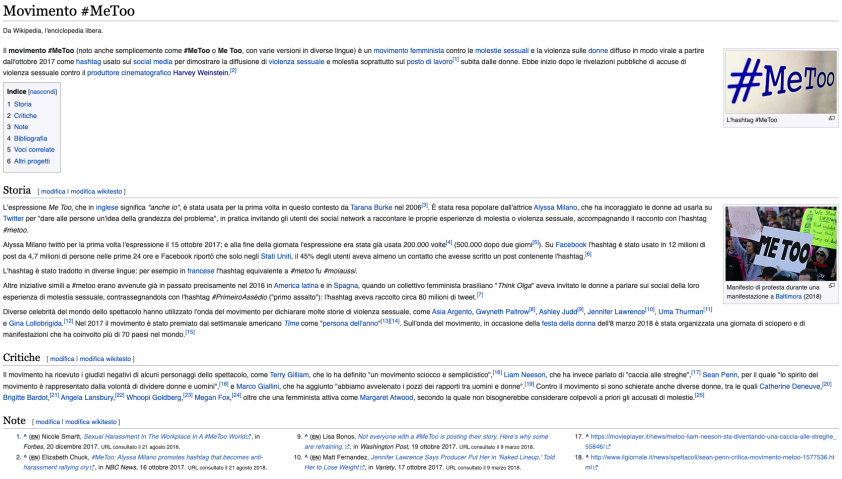
The main #MeToo movement page is offered in 64 languages, varying greatly in length, quality, and structure. Only 3 of the 64 languages, with English included, had a dedicated 'Purpose' section. By contrast, 46 of the 64 language versions carried a Criticism section. Indeed, the Italian version has the section as one of only two, the other being of history, as shown in Figure 5.18.

Some language versions offered localization to the local political, social, and feminist context of the country, either examining the particular hashtag version associated with that country, such as #jaztudi in the Slovenian page, or recording the moments where the movement gained traction in the country, such as the Danish page's section on TV presenter Sofie Linde, who spoke out about sexual abuse she had suffered in the entertainment industry.

Beyond the main #MeToo movement page, despite its recognition of the movement's impact across many countries, there were only 4 pages dedicated to the movement in the following respective countries: South Korea, China, India, and Pakistan. It is unclear why these four countries have such dedicated pages where others, no-

Figure 5.18

Italian #MeToo Page



Movimento #MeToo

Da Wikipedia, l'enciclopedia libera.

Il **movimento #MeToo** (noto anche semplicemente come **#MeToo** o **Me Too**, con varie versioni in diverse lingue) è un movimento femminista contro le molestie sessuali e la violenza sulle donne diffuso in modo virale a partire dall'ottobre 2017 come hashtag usato sui social media per dimostrare la diffusione di violenza sessuale e molestia soprattutto sul posto di lavoro[1] subita dalle donne. Ebbe inizio dopo le rivelazioni pubbliche di accuse di violenza sessuale contro il produttore cinematografico **Harvey Weinstein**.[2]

Indice [nascondi]
1 Storia
2 Critiche
3 Note
4 Bibliografia
5 Voci correlate
6 Altri progetti

L'hashtag #MeToo

Storia [modifica | modifica wikitesto]

L'espressione *Me Too*, che in inglese significa *"anche io"*, è stata usata per la prima volta in questo contesto da Tarana Burke nel 2006[3]. È stata resa popolare dall'attrice Alyssa Milano, che ha incoraggiato le donne ad usarla su Twitter per "dare alle persone un'idea della grandezza del problema", in pratica invitando gli utenti dei social network a raccontare le proprie esperienze di molestia o violenza sessuale, accompagnando il racconto con l'hashtag *#meToo*.

Alyssa Milano twittò per la prima volta l'espressione il 15 ottobre 2017; e alla fine della giornata l'espressione era stata già usata 200.000 volte[4] (500.000 dopo due giorni[5]). Su Facebook l'hashtag è stato usato in 12 milioni di post da 4,7 milioni di persone nelle prime 24 ore e Facebook riportò che solo negli Stati Uniti, il 45% degli utenti aveva almeno un contatto che avesse scritto un post contenente l'hashtag.[6]

L'hashtag è stato tradotto in diverse lingue: per esempio in francese l'hashtag equivalente a *#metoo* fu *#moiaussi*.

Altre iniziative simili a *#metoo* erano avvenute già in passato precisamente nel 2016 in America latina e in Spagna, quando un collettivo femminista brasiliano "*Think Olga*" aveva invitato le donne a parlare sui social della loro esperienza di molestia sessuale, contrassegnandola con l'hashtag *#PrimeiroAssédio* ("primo assalto"): l'hashtag aveva raccolto circa 80 milioni di tweet.[7]

Manifesto di protesta durante una manifestazione a Baltimora (2018)

Diverse celebrità del mondo dello spettacolo hanno utilizzato l'onda del movimento per dichiarare molte storie di violenza sessuale, come Asia Argento, Gwyneth Paltrow[8], Ashley Judd[9], Jennifer Lawrence[10], Uma Thurman[11] e Gina Lollobrigida.[12] Nel 2017 il movimento è stato premiato dal settimanale americano *Time* come "persona dell'anno"[13][14]. Sull'onda del movimento, in occasione della festa della donna dell'8 marzo 2018 è stata organizzata una giornata di sciopero e di manifestazioni che ha coinvolto più di 70 paesi nel mondo.[15]

Critiche [modifica | modifica wikitesto]

Il movimento ha ricevuto i giudizi negativi di alcuni personaggi dello spettacolo, come Terry Gilliam, che lo ha definito "un movimento sciocco e semplicistico";[16] Liam Neeson, che ha invece parlato di "caccia alle streghe",[17] Sean Penn, per il quale "lo spirito del movimento è rappresentato dalla volontà di dividere donne e uomini",[18] e Marco Giallini, che ha aggiunto "abbiamo avvelenato i pozzi dei rapporti tra uomini e donne".[19] Contro il movimento si sono schierate anche diverse donne, tra le quali Catherine Deneuve,[20] Brigitte Bardot,[21] Angela Lansbury,[22] Whoopi Goldberg,[23] Megan Fox,[24] oltre che una femminista attiva come Margaret Atwood, secondo la quale non bisognerebbe considerare colpevoli a priori gli accusati di molestie.[25]

Note [modifica | modifica wikitesto]

1. ^ (EN) Nicole Smarti, *Sexual Harassment In The Workplace In A #MeToo World\u200e*, in *Forbes*, 20 dicembre 2017. URL consultato il 21 agosto 2018.
2. ^ (EN) Elizabeth Chuck, *#MeToo: Alyssa Milano promotes hashtag that becomes anti-harassment rallying cry\u200e*, in *NBC News*, 16 ottobre 2017. URL consultato il 21 agosto 2018.
9. ^ (EN) Lisa Bonos, *Not everyone with a #MeToo is posting their story. Here's why some are refraining.\u200e*, in *Washington Post*, 19 ottobre 2017. URL consultato il 9 marzo 2018.
10. ^ (EN) Matt Fernandez, *Jennifer Lawrence Says Producer Put Her In 'Naked Lineup,' Told Her to Lose Weight\u200e*, in *Variety*, 17 ottobre 2017. URL consultato il 9 marzo 2018.
17. ^ https://movieplayer.it/news/metoo-liam-neeson-sta-diventando-una-caccia-alle-streghe_55846/\u200e
18. ^ http://www.ilgiornale.it/news/spettacoli/sean-penn-critica-movimento-metoo-1577536.html\u200e

tably the English-speaking Western countries, do not, even though the movement was stronger in those political contexts. Moreover, none of these pages had editions in more than 6 languages, and strikingly the South Korean #MeToo page does not even contain a version in Korean, begging the question as to whether the editors of the page are native or reside in the country.

These country-specific pages all adopt a list-like approach to describing the movement in the respective countries, centering around public allegations of sexual assault against typically well known public figures amongst different industries. This organization around industries is clear and intentional, providing a convenient structuring for an encyclopedic entry. However, there is a significant disconnect even between the several stated purposes within the main #MeToo page and the implied focus on accused men in these country-specific articles. The structure enables a convenient, atomized approach to documentation, whilst at the same time implicitly claiming that the most important outputs and events demanding attention as a result of #MeToo are the accused men, legal proceedings, due process, and false accusations.

Finally, a number of individual pages of figures associated with the movement around the world were examined. These were Ahn Hee-jung, Dustin Hoffman, Elizabeth Perkins, Judith Godrèche, Nana Patekar, Sung Jae-gi, Zhu Jun, and Harvey Weinstein. Most of the individual pages examined had many more language editions than the main movement page. As expected, the largest and most detailed article was that of Harvey Weinstein, with a large dedicated section to his sexual abuse, legal proceedings, and impacts on the film industry. Amongst the other page, however, whether they were legally convicted or not of sexual abuse, references to the #MeToo movement or their (alleged) sexual abuses were not mentioned in the beginning sections; that is, not deemed important enough to be referenced in a summary introduction to an individual. Further, sexual assault allega-

tions and any convictions are often placed very near the end of an article, with often little to no mention of the #MeToo movement. This is interestingly in contrast with, for example, victims of police violence and whose suffering has propelled Black Lives Matter protests: Philando Castille's page clearly states his killing's relation to the Black Lives Matter, but Dustin Hoffman's page has the words '#MeToo' nowhere in the main text.

5.7 Conclusion and Discussion

This study examined three arenas of digital memory to understand how digital memory of #MeToo has formed. How memory forms in public and collective spaces is highly contingent, and what these processes and outcomes look like remains an active area of research, particularly for hashtag campaigns that often lack a traditional social movement organization or leadership structure. The five datasets rallied as evidence in this study revealed much about the scope, format, messaging of #MeToo in digital memory. As much, if not more, can be said about what *absent* in the datasets examined as what was.

In curation, both U.S. and China collections were less comprehensive of their target material as they had intended. The U.S. collection is unfortunately not a comprehensive archive of digital #MeToo material in the U.S., and consequently privileged either more accessible or prominent voices and records. For example, news articles with archived captures comprised 171 items of the collection, already a very small sample of what the media landscape was in relation to #MeToo, public allegations of sexual assault, and legal proceedings thereafter, that received journalistic attention. The Harvard Crimson was accounted for nearly half of the news articles, legal bills were restricted to ones read at the House of Representatives rather than state-level or company-level laws and policies.

The China collection was even less comprehensive, containing only 31 items. Omissions were particularly noticeable in that some widely used social media in China that was central to the movement's inception there were missing (Zeng, 2020). Few news articles, from outlets based in China or elsewhere, were included.

Circulation of #MeToo memory on TikTok was markedly different from that of YouTube. Much more than any other digital medium examined, TikTok was replete with individual activists, survivors, and campaign groups publishing feminist perspectives, debunking rape myths of all kinds, disclosing personal experiences of sexual assault, ridiculing misogynistic practices and public comments, all under the banner of '#MeToo'. The hashtag serves a common touchstone, a reference point that communicates both to the viewer and organising algorithms what tradition of feminist expression it belongs to. These solidify both the legacy and continuity of the movement–at least partially–as a call to speak out and to raise consciousness (Boyle, 2019a). The tenor of the YouTube content was much that of individual feminists and activists speaking out, but rather much more

backlash type content, collectively representing and solidifying #MeToo as a simplistic anti-men, suffocating witch hunt.

Finally, claims about #MeToo on Wikipedia were often atomized, incomplete, and inconsistent across countries and languages. Much of the records kept relate to specific sexual assault allegations, convictions, and otherwise of legal proceedings in relation to typically high profile men. A reader introduced to #MeToo for the first time through Wikipedia, especially not in English, would likely be given the impression #MeToo was solely comprised of these allegations and legal proceedings. This atomization–the individual, bitesized contributions to articles–are the result of Wikipedia's verifiability criterion and openness of editing. Individual allegations will have numerous readily available sources to cite, where a more feminist perspective may be more difficult to be convincing of 'verifiability'. The openness of editing means individual editors typically contribute small parts rather than to any overarching narrative or commentary (Grabowski & Klein, 2023).

Overall, to answer the main research question: there is no one dominant narrative or singular memory of #MeToo. Across the platforms examined from social media to curated archives, massive variations in whose speech was recorded, what memory-making function that served, and recorded in what manner, were shaped by the affordances of each platform. None of the memories on any individual platform comprise the entirety of what #MeToo means in collective memory, but each capture a particular aspect and interpretation. Curated archives, with the most explicit focus on capturing a comprehensive record and memory, have fallen far short of this goal whether for technical, resource, or other shortages. Openly editable archives on Wikipedia, on the other hand, result in atomized, list-like records that intentionally or otherwise reinforce a 'take-down' memory of #MeToo, with memory beyond English editions on the U.S. sparse, poorly constructed, and little maintained. By contrast, TikTok and YouTube demonstrate a living memory of #MeToo, replete with possibility. TikTok across multiple countries, and especially French users, continue to utilise and champion '#MeToo' as a call to speak out, raise consciousness, and combat misogyny. Surprisingly little backlash to feminism on TikTok used the hashtag, in contrast with YouTube, where the disconnect between what survivors remember #MeToo to be and commentators who hold beliefs that #MeToo is variously the symptom of feminism 'gone too far' or simply the latest excuse for false accusations to be wantonly levied against powerful men. All of the above, and other platforms unexamined still, and all of curation, circulation, and claims comprise important parts of the digital memory of #MeToo.

A few further observations about the formation and state of collective memory of digital activism, feminist or otherwise, are worth mentioning. First, structure and leadership have been aspects deliberately left out of feminist activism (Freeman, 1972), and though Tarana Burke is the founder of the original Me Too movement, does

not attempt to or intend to speak for the #MeToo movement. This structurelessness is partially the reason the movement is an instance of connective action across countries that it may be spoken of as a 'global' movement, but may simultaneously be partially be the reason why memory and narrative surrounding the movement is as fragmented, varied, and disparate (Bennett & Segerberg, 2012; A. Park, 2017). Both supporters and detractors of a digital feminist campaign may project their interpretation and meaning onto the campaign.

Second, though both curated archives were found to be less comprehensive than intended, such archives, on the Internet Archive using the WayBack Machine or otherwise, serve an important role in the future of digital memory work for social movements. Unlike individual bloggers, advocacy organizations, and encyclopaedias, a curated archive has the following critical advantages. First, if nothing else many web pages are not available in their original form after 1 year (Costa et al., 2017). This consideration alone catapults the importance of curated archives where records of activism on the internet are likely to experience censorship. Second, curated archives may have better infrastructure to preserve web content. The Internet Archive is one such mechanism, but Reddit pages in the U.S. archive reveal at minimum an inconsistency in the archival technology, policy, or resourcing between different social media platforms: the Twitter archive they possess is collected through an application programming interface (API) allowing much more flexibility in data handling for future analyses. Perhaps in future greater collaboration between activists and archivists could facilitate improved records and curations. Further, both the U.S. and the China collection were curated by organizations based in the U.S.: this is symptomatic of the vast majority of web archives being collected and hosted by the global north (Costa et al., 2017). If we are truly to speak of global digital activism, we should take steps to also to have curated archives for many political contexts, particularly in the global south.

Third, evidence of evolving repertoires of political contention and therefore memory-making were evident (Tilly, 1977). The China collection revealed GitHub as one locus of memory work: indeed, a number of other repositories with similar goals and structure are easily accessible[5]. GitHub, in contrast to Wikipedia or Baidu in the Chinese context, is emerging as 'a collaborative yet centralized archiving and curation workflow' (E. L. Han, 2023, p.340) and has been used for the preservation of COVID-19 memories in addition to the archiving of feminist activism. On TikTok, it also became clear how the affordances of the audiovisual f2 ormat enabled richer, more varied options for survivors to record and express their own disclosures and understanding of #MeToo. These mechanisms are markedly different from the ones widely available and accessible at the inception of the movement in the U.S. in October 2017.

The memory of #MeToo is a living one and constantly being revised and solidified in various ways across plat-

[5] for example, https://github.com/china-public-events/metoo

forms. Participants and observers of future digital-born movements may do well to be conscious of memory-making practices in all of curation, circulation, and claims.

5.8 Limitations and Further Work

I note several limitations with the present study. First and foremost, the examined datasets are only able to reveal a snapshot of the digital collective memory of #MeToo. All data was captured in late 2023, and the evolution of how the movement lasts in collective memory in any given country, or globally, may yet shift. Such a limitation is inherent, though, to any archival research, just as it is indeed the construction of curated archives especially are bounded by planned project time spans, personnel, funding, expertise, and tools at hand. The inevitably snapshot nature of such work, however, paired with the living nature of #MeToo memory illustrated above and the generally noted ephemeral nature of content on social media, calls for further exploration to at minimum future snapshots to better understand these fleeting and varied flows.

Second, not only does the present study capture a temporal snapshot, the datasets examined are not a comprehensive overview of all digital memory in this period either. Sites with international capacity, reach, and contributions served as touchstones to understand collective memory, but much more exists within specific political contexts. South Korean feminism, for example, would not be fully represented without an examination of Womad (Koo, 2020), nor would Chinese feminism without Weibo (Liu, 2023). Egyptian #MeToo activism began on Instagram (Walsh, 2020). Even further, other digital media such as television, podcast, and radio were not considered. Memory is fluid, fragmented, multitudinous, ever-changing as is illustrated by the the selection of five datasets examined in this article. What I hope this has illustrated, however, is the need for wider, more holistic views of digital media, where often through convenience or other reasons we focus on specific easily accessible platforms.

Chapter 6

Conclusion

This thesis provides an account of the digital dynamics of #MeToo across the globe, organized around the central research question: What was the effect of #MeToo on international discourse on sexual violence? To do so, this thesis comprises three independent studies to examine different aspects of #MeToo as a global movement. First, Article I directly tackled the mechanisms of diffusion for the movement, finding that the dialogical framework of transnational diffusion operationalized to Twitter can explain some of the observed empirical behaviors of diffusion across languages (Chabot, 2010). Second, rape myths in news media have long been prevalent and a major site of change for #MeToo. Article II examined the dynamics of these rape myths in news media across languages and countries, finding that the prevalence of rape myths in news reports, though having declined in some countries for a period of time due to the movement, has not changed significantly across the world. Finally, Article III foregrounded the importance of memory formation in relation to social movements, finding that collective memory on #MeToo is fragmented and often incomplete.

This chapter summarizes the research findings across the three empirical chapters and synthesizes them in relation to the central research question. This conclusion chapter will also reflect on the limitations of the research, the challenges of a categorical approach to understanding organizational models of activism, and indicates areas for future research.

6.1 Contributions

This thesis makes contributions through the methodologies developed. Article I features a agent-based modeling, a less commonly used technique in computational social science and social movement studies. However, agent-based modeling is a powerful tool that supplies the researcher with high levels of control over the processes running in the model whilst producing non-linear and complex dynamics. This freedom to control the parameters, rules, and universe of interaction between agents gives a flexibility of operationalization to constructs and

processes specified in social movement theories. Critically, they are able to aid with explanations of emergent outcomes, in what researchers in genetic and evolutionary computation have named 'inverse generative social science' (Vu et al., 2019). Prior to this research, much of the theory surrounding social movement diffusion did not take into account the nuances introduced by the digital era. While Bennett and Segerberg's (2013) model of connective action highlighted the importance of personal expression shared over social networks, it fell short of theorizing specific mechanisms that underpin these dynamics. Furthermore, recent scholarship examining the transnational dimension of movements such as #MeToo often relied on correlational analyses of tweet volumes across countries, without delving into the mechanisms of diffusion or verifying the actual occurrence of these movements on digital platforms (e.g. Suk et al., 2023). Article I addressed these gaps by adopting a methodological setup that not only complements existing studies but also employed a longitudinal design, testing these processes across a three-year period. This approach not only lends greater credibility to the findings related to digital activism but also underscores the importance of understanding the decision-making process and the detailed construction of agent-based models.

Further, agent-based modeling's flexibility means adaptability across different platforms, a feature that has become increasingly important following Twitter's acquisition and re-branding to X that introduced significant structural changes impacting digital activism. The study's methodological innovations are particularly relevant for adapting to new platforms like TikTok, as suggested in Article III. This adaptation could involve incorporating parameters that account for not only the quantity of replies and interactions but also their qualitative aspects. This methodological contribution is critical for advancing our understanding of digital activism in an ever-evolving social media landscape, providing a robust framework for exploring the complex mechanisms of social movement diffusion in the digital age. I hope this that demonstration spurs further interest and research using such methodology.

Article II also contributes methodologically to media studies and feminist scholarship. First, the explicit focus on comparisons across languages and countries' media landscapes introduces a novel approach to understanding the global discourse around sexual assault, highlighting the importance of cultural and linguistic contexts in media representations. Second, the this work represents a relatively early adoption of very recent development in machine learning and 'artificial intelligence', namely GPT-4 for data augmentation. By augmenting data with GPT-4 and ensuring all augmented data were manually checked before subsequent analysis, this study maintains the integrity and reliability of its findings, the scope of analysis achieved was accordingly augmented that would have been a prohibitive limit before. Third, the application of Bayesian Structural Time Series to investigate changes in news media coverage of the #MeToo movement and public sexual assault allegations of-

fers an analytical tool that captures the complexity of media dynamics over time by enabling the separation of contributing components to the final signal of the frequency of rape myths over time.

In Chapter 2, the background scholarship of connective action that modern digital activism falls under was discussed. This thesis also makes theoretical contributions to connective action scholarship in explicitly considering and incorporating transnational diffusion, media relations, and collective memory within the paradigm of connective rather than collective action. Article I provides support for the dialogical framework of relational transnational diffusion of social movements, particularly in the context of social media channels like Twitter. That is, what are the granular mechanisms on new information communication channels that underpin the connective action mode of organization (Bennett & Segerberg, 2013)? Article II distills and synthesizes rape myths across writings from feminist scholars on the subject, unifying nomenclatures and categorizations often with some differences. This unification helps in creating a more coherent and powerful framework for understanding and combating rape myths. It also provides support for the 'protest paradigm' (Chan & Lee, 1984) and critically just how universal it is outside of the English-speaking world as well. Lastly, Article III bridges the gap between memory scholarship and social movement scholarship, a still developing area of scholarship. Combining the framework identifying three arenas of memory practices of claims, curations, and circulation (Merrill et al., 2020) with the lens of privileging practices (Burkey, 2020), Article III is able to capture a holistic view of memory-making by rallying five datasets across digital media. It reveals that social movement and memory scholars should continue to adopt holistic views across the digital spectrum of media affordances and platforms: only such a view can reveal the state of digital memory for social movements, but also enable comparisons between platforms and loci of memory. Moreover, a holistic approach best enables international comparisons: for example, Wikipedia editions in languages spoken in India featured bolder, stronger claims, but these languages were much less present in TikTok and YouTube.

The findings from each chapter do not stand in isolation. Article I underscores the significance of direct diffusion mechanisms, particularly highlighting the role of dialogue in the diffusion process. Article II provides evidence of the reluctance of news outlets–of which many prominent ones are owned by figures complicit in perpetuating rape culture (Durham, 2021)–indicating just how universal and entrenched patriarchal practices are. The emphasis on the communication between individuals resonates with the memory-making processes examined in Article III, which found that individual contributions to digital collective memory are not just supplementary but essential: without individual activist contributions to memory-making, institutional ones take precedence and attention, whether that is of curated archives, the emergent result of encyclopedic entry policies, or institutionally produced documentaries. If activists of future digital movements wish to be in greater

control of these outcomes, both direct dialogue and direct contributions to all memory practices will be important. Indeed, direct dialogue about past memories and previous activism can alter the efficacy of present activism (Whitlinger, 2021).

Furthermore, the findings presented in Articles II and III reveal a stark contrast in the role of traditional institutions like news media and universities, which are neither the recipients nor the progenitors of change within the context of #MeToo. Article II delineates the entrenched misogynistic practices within journalism and academia across various countries, cultures, and levels of political openness, highlighting their resistance to transformation. Similarly, Article III's examination of curated archives of digital #MeToo content and Wikipedia's archiving practices illustrates the limited control activists have over narrative construction, pointing to a partial and often resistant engagement with these narratives by traditional institutions.

Lastly, apparent throughout the three articles is the double-edged property of digital activism's structurelessness. Importantly, the structurelessness meant here goes beyond the that seen particular of feminist movements (Freeman, 1972), but rather the necessary decentralized nature of 'little of nor formal organizational coordination of action' inherent to these new forms of activism (Bennett & Segerberg, 2013, p.47). This structurelessness, and also lack of clear leadership, is simultaneously facilitating of rapid diffusion as seen in Article I and more generally has profound effects on participation, but also limiting in the agency and coordinated effect on other realms of activism, particularly in the realm of news reporting and the construction of collective memories about #MeToo as seen in Articles II and III respectively. This openness allows for a wide projection of meaning onto the movement, enabling not only diverse interpretations but also the appropriation of the narrative by deeply misogynistic groups and commentators. This phenomenon underscores the complexity of digital activism, where its very strengths can also serve as avenues for its undermining, necessitating a nuanced understanding and strategic navigation of the digital terrain by activists. This phenomenon is not newly observed, certainly: Gerbaudo (2017) strenuously contends that this growing consensus that contemporary movements are characterized by a type of structurelessness and further that there is an emerging *fear* of leadership needs to be confronted. Gerbaudo argues for this on the basis of of ethical and political dangers of unaccountable and informal leadership structures. I hope more simply, through the results of Article II and especially Article III, to draw attention to additional effects observable: whatever the ethical and political dangers, how a movement's memory persists will also have tangible and possibly more influential effects. Accounts in future of digital activism may take these considerations into account. This leads naturally on to the next section on some overall limitations.

6.2 Limitations

Here I note some limitations of the research programme carried out in this thesis and propose avenues for future research. Both articles I and II utilized computational methods to analyze data across diverse political and cultural contexts, an approach that, while innovative and revealing, is not without its shortcomings. Any computational analysis necessitates a distant, organizing, and categorizing procedure that imposes a layer of visibility and invisibility, of relevance and irrelevance, upon the data observed (Haraway, 1988). Indeed the decision of *what* data is worth examining in the first place is no trivial question (D'Ignazio & Klein, 2020). In the context of the studies presented here, this has at least meant that the nuanced, contextual meanings of phenomena like the #MeToo movement are at risk of being flattened or homogenized. Though a major motivation for the work is to examine the international reach and dynamics of #MeToo, it is nevertheless essential to underscore the tradeoffs in doing so. The #MeToo movement is not a monolithic entity: its manifestations and implications vary significantly across different cultures and political landscapes. That '#MeToo' had a widely international spread and sparked conversation and political activism is undoubtedly true, how accurate is that depiction (A. Park, 2017)?

#MeToo is not monolithic, nor is it an isolated instance of feminist activism in any country where it was present. Feminism in South America, for example, has always been based on an understanding f the politics and structure of violence in a system deeply interwoven and inseparable from the oppression of women (Frayssinet, 2018): femicide protests are regularly held and were done so before #MeToo: Ni Una Menos had its first demonstration organized in the wake of a 14-year old Chiara Paez beaten to death by her boyfriend in 2015. #MeToo has had limited reach in Japan possibly in relation to the cultural setting into which the movement was introduced: Japanese survivors have expressed a conflict between the strong emotional appeal of personal sexual violence disclosures of the movement and the reservedness and conflict avoidance associated with perceived Japaneseness (Mizoroki et al., 2023). Chinese feminism suffers heavy censorship (Liu, 2023). Some felt that in France, sometimes portrayed as a home of romantic love and more liberal sexual expression, the #MeToo movement was 'skipped' (Kuper, 2021).

Not only do the contexts and histories vary across counties, so do the platforms and sites of feminism and protest: in Egypt, the movement was more prominently associated with Instagram (Walsh, 2020); in Korea, Megalia and Womad are key (Koo, 2020); in China, as found in Article III, GitHub may become increasingly relevant (E. L. Han, 2023).

This thesis endeavors, therefore, to be in conversation with and in complement to the qualitative analyses that

are better able to examine these cultural, social, and political particularities. This thesis contends, naturally, that there is some value in making this trade-off. Core to the design and business model of many digital platforms and media is international buy-in and usage, and therefore the mediation of digital dynamics of transnational movements in the internet age by these platforms are technologies is inevitable and demanding of attention. Indeed, it is hoped Article III mitigates some of this tradeoff and presents a more balanced perspective. Future work might apply interdisciplinary methodologies that combine computational techniques with qualitative, context-sensitive analyses.

Given its wide ranging impacts and its use in Article II, I make a short note regarding Large Language Models (LLMs) and generative AI in relation to social movement research and computational social science. It is likely that they will bring important changes to the discipline, and as researchers continue to explore and experiment with these technologies, the areas where they can add the most value will become increasingly apparent. Here I will one brief example as used in Article II: data augmentation, which proves particularly beneficial for tasks requiring high-quality annotations that can be difficult to obtain. The quality of annotations for training data is always important, but especially so in social science research because this quality of data annotations not only impact model performance but construct validity and the how well operationalization of a concept into a measure can and is achieved (Bryman, 2012). For text augmentation especially, LLMs' possess the ability to grasp context can be a great boon in utility over older BERT models. For example, rape myths are known to be pervasive (Franiuk, Seefelt, Cepress, & Vandello, 2008; Kitzinger, 2004). How and where do they manifest? They could manifest in a single sentence, with an explicit statement like 'she was clearly asking for it with what she wore that night', or it might be an underlying tone and framing of a paragraph or entire article. BERT models are not able to work with these differences without substantial prior knowledge and setup from the researcher. By contrast, an LLM could be properly instructed to look for relevant material anywhere in a given piece of text, or extract a narrative.

But none of these are guaranteed improvements or solutions, and many open questions need to be addressed in the coming usage of LLMs within computational social science. First, on the example of capturing narratives or framing devices with an LLM, this is not a simple matter of prompt engineering: much validation will careful academic attention will be required of the outputs of any given prompt to extract rape myth(s) from text.

Second, the foregoing is not to say that the prompt engineering itself will be straightforward: how can models of this size be properly instructed, fine-tuned, or trained to properly attend to specific constructs within social sciences? Scholars at often at pains to delineate the shape of a concept or term in complex and subtle ways, and how any particular conception of a commonly used concept or term may be properly communicated in a

prompt is not trivial. What *is* a narrative?

Additionally, outputs can be highly variable and how the outputs vary with differences in input is rarely obvious. That is, it will be difficult to know when one has achieved a good, great, or the best prompt. These difficulties exist without needing to invoke the the commonly discussed 'hallucination' problem of the inconsistencies between an LLM's output and reality, a problem that some deem to be ineluctable (Xu et al., 2024). The problem, then, is at least in part epistemological: how can researchers reliably *know* the quality of outputs of an LLM? This problem is much greater in severity in comparison with BERT models, if nothing else simply because of the possible information and states an LLM can assume, by virtue of being *large* language models with parameter counts orders of magnitude larger. Moreover, often larger, commercial models will refuse to generate or accept prompts in relation to sensitive content, especially anything to do with sex even if for clear academic purposes. This was a problem in Article II for some data augmentation.

Third, assuming the accomplishment of such a validation process, should that effort be sold or incorporated into LLMs being produced? Perhaps that might go some way to combat the reams of misogyny present and documented across so much of the internet that LLMs are trained on. Finally, the nomenclature of 'generative' AI should not be taken at face value to mean 'generative', 'synthesizing', or 'imaginative' in any meaningful way: LLMs, like any other machine learning model, are trained on defined sets of inputs and outputs, and are not capable–and possibly not permitted to, for commercial, reputational, and safety reasons–to speculate on new perspectives: researchers should be aware LLMs will not be able to do the qualitative ideation critical to theoretical advancement. At heart, LLMs produce sophisticated syntactic manipulations based on matrix multiplications, and whether this architecture can ever produce the semantic understanding that is required to handle *concepts* rather than *words* has been hotly debated for decades (cf. Searle, 1980).

6.3 Concluding Remarks

This thesis sought to answer the research question:

> What was the effect of #MeToo on international discourse on sexual violence?

#MeToo has left an indelible mark on international discourse in many countries, but its story is far from over. The movement has been longstanding and prevalent enough to be the subject of diffusion across social media channels, change–albeit temporarily–how sexual violence and assault are portrayed in media, and be a consistently invoked term both as a watershed moment, continued use as a talismanic call to speak out, and in making of collective memory. The movement's impact is momentous and living not just through often asso-

ciated public allegations and convictions but through the sheer volume of survivors speaking out beyond in the English-speaking world and elsewhere, the challenges to patriarchal status quos, all while simultaneously amorphous and without structural leadership. As we move further away from the #MeToo moment of 2017, activists and scholars should remember not only that digital memories make things never truly forgotten, but also that mobilizations long past continue to shape current political debates (Accornero, 2019; Cheng & Yuen, 2019), and the same may yet be true of #MeToo. As one of the most enduring forms of digital feminist activism in recent times, there is no better time than the present to use it–or the memory of it–to study and effect change against societal and institutional misogyny around the world, whether through digital means or otherwise.

Just as the movement is not monolithic across countries and political contexts, it is also not the first and certainly not the last of digital feminist activism, let alone feminist activism more broadly. Some previous campaigns were already mentioned in Chapter 1 : *SlutWalk* (Mendes, 2015), #GirlsLikeUs (2012), #YesAllWomen (2014), #BringBackOurGirls (2014) were some before #MeToo. Many campaigns have come since, for example #SeeFemaleWorkers in China (Y. Wang & Tavmen, 2024) and #DontTellMeHowToDress in Thailand (Chintrakarn, 2024). Examination of #MeToo may shed light on the digital dynamics of subsequent mobilizations.

6.3.1 Ethics and Positionality

This DPhil research was approved with approval reference SSH_OII_CIA_21_082 by the Social Sciences and Humanities Interdivisional Research Ethics Committee (IDREC) at the University of Oxford. Further, I undertook research integrity training courses designed and administered by the Social Sciences and Humanities Division, and throughout I followed the University's Best Practice Guidance for Internet-mediated research and Association of Internet Research Ethics. As part of that approval process, the following considerations of data collection and storage were stated and kept throughout the project. The datasets core to the analysis in Articles I and III contained posts and content form individual on social networking sites. Only posts that the authors themselves have made publicly available were be collected (excluding, therefore, 'private' accounts that are available to restrict the possible audience). In keeping with common practice in amongst internet researchers, these posts were not collected with informed consent of the authors of these posts as the obtaining of informed consent with the large number of users was not considered practicable. Therefore, all data processing was conducted primarily on University remote Advanced Research Computing facilities with robust security and data storage policies, or occasionally locally on my personal computer that is password-secured and never left unattended or unlocked in public spaces. Further, personally identifiable information–as much as was possible to reasonably quickly filter out–was removed before any analysis was conducted. In Article I, this means that no names, profile pictures, or locations were used in the agent-based modeling analysis; names and biogra-

phies were used only to infer gender and whether a user was an individual or organization using an available pre-trained model and never used again (Z. Wang et al., 2019); model inference was also again strictly local and offline. For Article III, a similar process was followed for data storage. All files were named by unique, impersonal video id or randomly generated unique document id such that I would not know the authors of posts during the qualitative annotation process, save for when it was clearly stated in the content itself. Quotes and pictures for figures in Article III were truncated and anonymized as much as possible whilst preserving relevant information. Only quotes that are embedded text in videos were chosen as they are much more difficult for anyone to match to authors through a string-search.

No data collected for any part of this DPhil is to be published, even though the sources are all publicly available. This is to avoid organizing data in a manner that may be misused, especially so in Articles I and III for individuals who have disclosed experiences of sexual assault or violence: collating such data may run the risk of creating a list of survivors that may be abused or misused in some way, particularly when their user timeslines are also collected. All data will be destroyed securely in accordance with the guidelines mentioned above.

The handling of research data also demanded considerations of psychological safety for myself and Joana Perrone as my collaborator in Article II. For Articles I and III, I was necessarily continuously exposed to large volumes of possibly distressing disclosures of sexual violence, online harassment of survivors and activists, affecting imagery, hate speech, and generally sexually explicit content. To safeguard against some of the psychological effects these may have, I participated regularly in the Social Sciences Division Wellbeing seminars and training workshops. I had regular discussions during these annotation works with my supervisors to monitor my experience and wellbeing, and consulting psychological professionals where I felt appropriate. Further, I had a network of support of fellow doctoral candidates within the department but also within the Project on Democracy and Technology (DemTech), where a network of support arose due to our research on misinformation that also demanded safeguarding of researcher wellbeing. For Article II, we were explicitly interested finding rape myths, reading multiple times over them, understanding them, and reflecting on the categories with which we classified them. During our regular reviews of material we had both annotated, we ensured there was space to reflect on the process and its impact on ourselves, and made adjustments and accommodations for each other whenever the need arose. The whole DPhil process in this regard was sometimes difficult, especially along the way having learned more about and continuously seen more manifestations of sexist and patriarchal power structures in my data and in everyday life. Throughout, I found it important also personally to remind myself that the work was valuable, that researchers around the world share some of these struggles.

Finally, I reflect on my positionality as a self-identifying male researcher delving research on topics of #MeToo,

gender, sexual assault, and harassment. The vast majority of survivors and that #MeToo is about and for are women, and the experiences of women survivors of sexual violence are inaccessible to me. I possess the privilege to be able to walk through life without having to endure many of these lived experiences, from quotidian misogyny to extreme abuse. I bring, therefore, a position of privilege and distance that may have influenced the analysis and work presented here. I also possessed particular positionality as a *researcher*. As I have noted elsewhere in this thesis, the implicit organizing of information in the world that we refer to as 'data' determines what is seen and not seen. Therefore, it is an exercise of power and privilege in itself, especially as it connects to the long history of a conflation between the male view and an 'objective'one (Haslanger, 1995). As with Wikipedia being an active and not passive producer of knowledge, I recognize that the process of research is a living part of knowledge production and not separate from it. To try to mitigate these potential effects, I did the following. On a personal level, I strove to consistently read relevant material, self-educate, critically reflect upon, and adjust my actions and attitudes to become a better feminist in practice which I hope then is reflected in the process and outcome of the research. Academically, I strove to ground my work wherever relevant with feminist thought and scholarship: drawing on examples of feminist transnational diffusion (Roggeband, 2010) in ideation of and research design for Article I, through the synthesis of rape myths in Article II that foregrounded existing typologies and categorizations of women's experiences, and the collaboration in the qualitative coding of Article II in the execution of actually *identifying* rape myths, and through the focus of when and how survivors' stories were told or omitted in Article III. Where possible, I also actively sought feedback from women colleagues and scholars. I hope this thesis contributes something nonetheless.

References

Accornero, G. (2019). 'I wanted to carry out the revolution': Activists' trajectories in Portugal from dictatorship to democracy. *Social Movement Studies*, *18*(3), 305–323. https://doi.org/10.1080/14742837.2018.1560258

AFP. (2018, October). #MeToo in Europe: New laws on consent and catcalling. Retrieved August 18, 2023, from https://www.thelocal.fr/20181006/metoo-in-europe-new-laws-on-consent-and-catcalling

Ahmed, S. (2010). *The Promise of Happiness*. Durham University Press.

Alcoforado, A., Ferraz, T. P., Gerber, R., Bustos, E., Oliveira, A. S., Veloso, B. M., Siqueira, F. L., & Costa, A. H. R. (2022). ZeroBERTo: Leveraging Zero-Shot text classification by topic modeling. Retrieved March 14, 2024, from http://arxiv.org/abs/2201.01337

Alshaabi, T., Dewhurst, D. R., Minot, J. R., Arnold, M. V., Adams, J. L., Danforth, C. M., & Dodds, P. S. (2021). The growing amplification of social media: Measuring temporal and social contagion dynamics for over 150 languages on twitter for 2009–2020. *EPJ Data Science*, *10*(1), 15. https://doi.org/10.1140/epjds/s13688-021-00271-0

Andalibi, N., Morris, M. E., & Forte, A. (2018). Testing waters, sending clues: Indirect disclosures of socially stigmatized experiences on social media. *Proceedings of the ACM on Human-Computer Interaction*, *2*(CSCW), 1–23. https://doi.org/10.1145/3274288

Aral, S., & Nicolaides, C. (2017). Exercise contagion in a global social network. *Nature Communications*, *8*, 1–8. https://doi.org/10.1038/ncomms14753

Armstrong, E. A., & Crage, S. M. (2006). Movements and memory: The making of the Stonewall myth. *American Sociological Review*, *71*(5), 724–751. https://doi.org/10.1177/000312240607100502

Ashley, L., & Olson, B. (1998). Constructing reality: Print media's framing of the women's movement, 1966 to 1986. *Journalism & Mass Communication Quarterly*, *75*(2), 263–277. https://doi.org/10.1177/107769909807500203

Ashuri, T. (2011). Joint memory: ICT and the rise of moral mnemonic agents. In M. Neiger, O. Meyers, & E. Zandberg (Eds.), *On Media Memory: Collective Memory in a New Media Age* (pp. 104–113). Palgrave Macmillan UK. https://doi.org/10.1057/9780230307070_8

Askanius, T., & Hartley, J. M. (2019). Framing gender justice. *Nordicom Review*, *40*(2), 19–36. https://doi.org/10.2478/nor-2019-0022

Azer, E., Harindranath, G., & Zheng, Y. (2019). Revisiting leadership in information and communication technology (ICT)-enabled activism: A study of Egypt's grassroots human rights groups. *New Media & Society*, *21*(5), 1141–1169. https://doi.org/10.1177/1461444818821375

Banet-Weiser, S., & Maddocks, S. (2023, August). Networked misogyny on TikTok: A critical conjuncture. In K. Boyle & S. Berridge (Eds.), *The Routledge Companion to Gender, Media and Violence* (1st ed., pp. 369–379). Routledge. Retrieved November 30, 2023, from https://www.taylorfrancis.com/books/9781003200871

Banet-Weiser, S., & Miltner, K. M. (2016). #MasculinitySoFragile: Culture, structure, and networked misogyny. *Feminist Media Studies*, *16*(1), 171–174. https://doi.org/10.1080/14680777.2016.1120490

Barrie, C., & Frey, A. (2021). Faces in the crowd: Twitter as alternative to protest surveys (B. Guidi, Ed.). *PLOS ONE*, *16*(11), e0259972. https://doi.org/10.1371/journal.pone.0259972

Belotti, F., Bernardini, V., & Comunello, r. (2023, August). Hashtag feminism straddling the Americas: A comparison between #NiUnaMenos and #MeToo. In K. Boyle & S. Berridge (Eds.), *The Routledge Companion to Gender, Media and Violence* (1st ed., pp. 531–542). Routledge. https://doi.org/10.4324/9781003200871

Benedict, H. (1993). *Virgin or Vamp: How the Press Covers Sex Crimes*. Oxford University Press. Retrieved December 18, 2020, from http://site.ebrary.com/id/10087198

Bennett, W. L., & Segerberg, A. (2012). The logic of connective action: Digital media and the personalization of contentious politics. *Information, Communication & Society*, *15*(5), 739–768. https://doi.org/10.1017/CBO9781139198752

Bennett, W. L., & Segerberg, A. (2013). *The logic of connective action*. Cambridge University Press.

Berlant, L. (1988). The female complaint. *Social Text*, *19/20*, 237–259. https://doi.org/10.2307/466188

Bimber, B. (2017). Three prompts for collective action in the context of digital media. *Political Communication*, *34*(1), 6–20. https://doi.org/10.1080/10584609.2016.1223772

Bimber, B., Flanagin, A. J., & Stohl, C. (2005). Reconceptualizing collective action in the contemporary media environment. *Communication Theory*, *15*(4), 365–388. https://doi.org/10.1111/j.1468-2885.2005.tb00340.x

Black Lives Matter. (2024). *Wikipedia*. Retrieved March 16, 2024, from https://en.wikipedia.org/w/index.php?title=Black_Lives_Matter&oldid=1212957848

Blank, G., & Lutz, C. (2017). Representativeness of social media in Great Britain: Investigating Facebook, Linkedin, Twitter, Pinterest, Google+, and Instagram. *American Behavioral Scientist*, *61*(7), 741–756. https://doi.org/10.1177/0002764217717559

Blasi, G. (2019, October). #Quellavoltache, Italy's #MeToo before #MeToo. Retrieved August 18, 2023, from https://giuliablasi.medium.com/quellavoltache-italys-metoo-before-metoo-83e7f6a73276

Bohner, G., Jarvis, C. I., Eyssel, F., & Siebler, F. (2005). The causal impact of rape myth acceptance on men's rape proclivity: Comparing sexually coercive and noncoercive men. *European Journal of Social Psychology*, *35*(6), 819–828. https://doi.org/10.1002/ejsp.284

Boitel, E., Mohasseb, A., & Haig, E. (2023). A comparative analysis of GPT-3 and BERT models for text-based emotion recognition: Performance, efficiency, and robustness. *Advances in Computational Intelligence Systems*. https://www.uk-ci.org/home

Boyd, A., & McEwan, B. (2022). Viral paradox: The intersection of "me too" and #MeToo. *New Media & Society*, *0*(0). https://doi.org/10.1177/14614448221099187

Boyle, K. (2019a). *#MeToo, Weinstein and Feminism*. Palgrave Macmillan.

Boyle, K. (2019b). What's in a name? Theorising the inter-relationships of gender and violence. *Feminist Theory*, *20*(1), 19–36. https://doi.org/10.1177/1464700118754957

Boyle, K., & Rathnayake, C. (2020). #HimToo and the networking of misogyny in the age of #MeToo. *Feminist Media Studies*, *20*(8), 1259–1277. https://doi.org/10.1080/14680777.2019.1661868

Brinson, S. L. (1989). TV rape: Television's communication of cultural attitudes toward rape. *Women's Studies in Communication*, *12*(2), 23–36. https://doi.org/10.1080/07491409.1989.11089734

Brodersen, K. H., Gallusser, F., Koehler, J., Remy, N., & Scott, S. L. (2015). Inferring causal impact using Bayesian structural time-series models. *The Annals of Applied Statistics*, *9*(1). https://doi.org/10.1214/14-AOAS788

Bronstein, C. (2005). Representing the third wave: Mainstream print media framing of a new feminist movement. *Journalism & Mass Communication Quarterly*, *82*(4), 783–803. https://doi.org/10.1177/107769900508200403

Brownmiller, S. (1975). *Against our will: Men, women, and rape*. Simon and Schuster.

Brunner, E., & Partlow-Lefevre, S. (2020). #MeToo as networked collective: Examining consciousness-raising on wild public networks. *Communication and Critical/Cultural Studies*, 1–17. https://doi.org/10.1080/14791420.2020.1750043

Bryman, A. (2012). *Social research methods* (4th ed). Oxford University Press.

Buechler, S. M. (1990). *Women's movements in the United States: Woman suffrage, equal rights, and beyond*. Rutgers University Press.

Burkey, B. (2020). Repertoires of remembering: A conceptual approach for studying memory practices in the digital ecosystem. *Journal of Communication Inquiry*, *44*(2), 178–197. https://doi.org/10.1177/0196859919852080

Bursztynsky, J. (2021). TikTok says 1 billion people use the app each month. *CNBC*. Retrieved March 14, 2024, from https://www.cnbc.com/2021/09/27/tiktok-reaches-1-billion-monthly-users.html

Burt, M. R. (1980). Cultural Myths and Supports for Rape. *Journal of Personality and Social Psychology*, *38*(2), 217–230.

Burt, M. R. (1991). Rape myths and acquaintance rape. In A. Parrot & L. Bechhofer (Eds.), *Acquaintance rape: The hidden crime* (pp. 26–40). Wiley.

Cacciatore, M. A., Scheufele, D. A., & Iyengar, S. (2016). The end of framing as we know it ...and the future of media effects. *Mass Communication and Society*, *19*(1), 7–23. https://doi.org/10.1080/15205436.2015.1068811

Camilleri, C. (2020). #MeTooSTEM: We must do more to protect women. Retrieved April 5, 2024, from https://www.um.edu.mt/library/oar/handle/123456789/66982
Accepted: 2021-01-12T05:54:43Z.

Carrignon, S., Brughmans, T., & Romanowska, I. (2020). Tableware trade in the Roman east: Exploring cultural and economic transmission with agent-based modelling and approximate Bayesian computation (S. Lozano, Ed.). *PLOS ONE*, *15*(11), e0240414. https://doi.org/10.1371/journal.pone.0240414

Caswell, M. (2015). Documenting south Asian American struggles against racism: Community archives in a post-9/11 world. In A. Reading & T. Katriel (Eds.), *Cultural memories of nonviolent struggles: Powerful times* (pp. 188–204). Palgrave Macmillan UK. https://doi.org/10.1057/9781137032720_10

Centola, D., & Macy, M. (2007). Complex contagions and the weakness of long ties. *American Journal of Sociology*, *113*(3), 702–734. https://doi.org/10.1086/521848

Chabot, S. (2010). Dialogue matters: Beyond the transmission model of transnational diffusion between social movements. In R. K. Givan, K. M. Roberts, & S. Soule (Eds.), *The Diffusion of Social Movements: Actors, Mechanisms, and Political Effects* (pp. 99–124). Cambridge University Press.

Chadwick, A. (2017). *The hybrid media system: Politics and power* (2nd edition). Oxford university press.

Chan, J. M., & Lee, C. C. (1984). The journalistic paradigm on civil protests: A case study of Hong Kong. In A. Arno & W. Dissanayake (Eds.), *News media in national and international conflict* (pp. 183–202). Routledge.

Chang, A. (2023, December). Feminist resistance on Chinese social media. In *Women's agency and mobile communication under the radar* (1st ed., pp. 225–237). Routledge. https://doi.org/10.4324/9781003304197-24

Cheng, E. W., & Yuen, S. (2019). Memory in movement: Collective identity and memory contestation in Hong Kong's Tiananmen vigils. *Mobilization: An International Quarterly*, *24*(4), 419–437. https://doi.org/10.17813/1086-671X-24-4-419

Chenou, J.-M., & Cepeda-Másmela, C. (2019). #NiUnaMenos: Data activism from the Global South. *Television & New Media*, *20*(4), 396–411. https://doi.org/10.1177/1527476419828995

Chidgey, R. (2015). 'A modest reminder': Performing suffragette memory in a British feminist webzine. In A. Reading & T. Katriel (Eds.), *Cultural memories of nonviolent struggles* (pp. 52–70). Palgrave Macmillan UK. https://doi.org/10.1057/9781137032720_11

Chien, A. C. (2023). Taiwan faces a #MeToo wave, set off by a Netflix hit. *The New York Times*. Retrieved August 2, 2023, from https://www.nytimes.com/2023/06/25/world/asia/taiwan-harassment-metoo.html

Chintrakarn, C. (2024). Thai-fusion popular feminism: The beginning of #DontTellMeHowToDress on Instagram. *Feminist Media Studies*, *0*(0), 1–18. https://doi.org/10.1080/14680777.2024.2329964

Citron, D. K. (2014). *Hate crimes in cyberspace*. Harvard University Press.

Clark, C. (2015). *#TrendingFeminism: The impact of digital feminist activism* [Master's thesis, The George Washington University]. Retrieved April 20, 2020, from https://search.proquest.com/docview/1691802140/abstract/DF4C5D30C8634F69PQ/1

Comunello, F., Mulargia, S., & Parisi, L. (2016). The 'proper' way to spread ideas through social media: Exploring the affordances and constraints of different social media platforms as perceived by Italian activists. *The Sociological Review*, *64*(3), 515–532. https://doi.org/10.1111/1467-954X.12378

Costa, M., Gomes, D., & Silva, M. J. (2017). The evolution of web archiving. *International Journal on Digital Libraries*, *18*(3), 191–205. https://doi.org/10.1007/s00799-016-0171-9

Crenshaw, K. (1989). Demarginalizing the intersection of race and sex: A black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics. *University of Chicago Legal Forum*, *78*(2), 147–156. https://doi.org/10.1016/0011-9164(90)80039-E

Crocamo, C., Viviani, M., Famiglini, L., Bartoli, F., Pasi, G., & Carrà, G. (2021). Surveilling COVID-19 emotional contagion on Twitter by sentiment analysis. *European Psychiatry*, *64*(1), e17. https://doi.org/10.1192/j.eurpsy.2021.3

Cuklanz, L. (2020). Problematic news framing of #MeToo. *The Communication Review*, *23*(4), 251–272. https://doi.org/10.1080/10714421.2020.1829302

Dalton, R., Van Sickle, A., & Weldon, S. (2010). The individual–institutional nexus of protest behaviour. *British Journal of Political Science*, *40*(1), 51–73. https://doi.org/10.1017/S000712340999038X

Daphi, P., & Zamponi, L. (2019). Exploring the movement-memory nexus: Insights and ways forward. *Mobilization: An International Quarterly*, *24*(4), 399–417. https://doi.org/10.17813/1086-671X-24-4-399

Davis, J. L., & Chouinard, J. B. (2016). Theorizing affordances: From request to refuse. *Bulletin of Science, Technology & Society*, *36*(4), 241–248. https://doi.org/10.1177/0270467617714944

De Cesari, C., & Rigney, A. (2014). Introduction. In C. De Cesari & A. Rigney (Eds.), *Transnational memory: Circulation, articulation, scales* (pp. 1–28). De Gruyter.

De Choudhury, M., Jhaver, S., Sugar, B., & Weber, I. (2016). Social media participation in an activist movement for racial equality. *Proceedings of the 10th International Conference on Web and Social Media, ICWSM 2016*.

de Souza, N. M. F., & Rodrigues Selis, L. M. (2022). Gender violence and feminist resistance in Latin America. *International Feminist Journal of Politics*, *24*(1), 5–15. https://doi.org/10.1080/14616742.2021.2019483

de Almeida, H. B. (2019). From shame to visibility: Hashtag feminism and sexual violence in Brazil. *Sexualidad, Salud y Sociedad (Rio de Janeiro)*, (33), 19–41. https://doi.org/10.1590/1984-6487.sess.2019.33.02.a

Della Porta, D., & Diani, M. (2020). *Social movements: An introduction* (Third edition). Wiley-Blackwell.

Della Porta, D., & Fillieule, O. (2004). Policing social protest. In D. A. Snow, S. A. Soule, & H. Kriesi (Eds.), *The Blackwell companion to social movements* (pp. 217–241). Blackwell Publishing.

Denzin, N. K. (1970). *The research act in sociology: A theoretical introduction to sociological methods*. Butterworths.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *arXiv:1810.04805 [cs]*. Retrieved April 30, 2020, from http://arxiv.org/abs/1810.04805

Diani, M. (1992). The concept of social movement. *The Sociological Review*, *40*(1), 1–25. https://doi.org/10.1111/j.1467-954X.1992.tb02943.x

D'Ignazio, C., & Klein, L. F. (2020). *Data feminism*. The MIT Press.

Dixon, K. (2014). Feminist online identity: Analyzing the presence of hashtag feminism. *Journal of Arts and Humanities*, *3*(7), 34–40.

Durham, M. G. (2021). *MeToo: The impact of rape culture in the media*. Polity Press.

Dwyer, T., Easteal, P., & Hopkins, A. (2012). Did she consent? *Alternative Law Journal*, *37*(4), 249–253. https://doi.org/10.1177/1037969X1203700407

Eagle, J. (2019, October). CA Gov. signs all 3 ERA #MeToo bills into law. Retrieved March 14, 2024, from https://www.equalrights.org/news/ca-gov-signs-all-3-era-metoo-bills-into-law/

Earl, J. (2010). The dynamics of protest-related diffusion on the web. *Information, Communication & Society*, *13*(2), 209–225. https://doi.org/10.1080/13691180902934170

Earl, J., & Kimport, K. (2011). *Digitally enabled social change: Activism in the internet age*. MIT Press. OCLC: ocn639573767.

Edgerton, G. R. (2020, February). The past is now present onscreen: Television, history, and collective memory. In J. Wasko & E. R. Meehan (Eds.), *A Companion to Television* (1st ed., pp. 79–103). Wiley. https://doi.org/10.1002/9781119269465.ch4

Entman, R. M. (1993). Framing: Toward clarification of a fractured paradigm. *Journal of Communication*, *43*(4), 51–58. https://doi.org/10.1111/j.1460-2466.1993.tb01304.x

Essayag, S. (2017). *From commitment to action: Policies to end violence against women in Latin America and the Caribbean* (tech. rep.). UNDP and UN Women. Panama.

Feild, H. S. (1978). Attitudes toward rape: A comparative analysis of police, rapists, crisis counselors, and citizens. *Journal of Personality and Social Psychology*, *36*(2), 156–179. https://doi.org/10.1037/0022-3514.36.2.156

Feng, F., Yang, Y., Cer, D., Arivazhagan, N., & Wang, W. (2022, March). Language-agnostic BERT sentence embedding. https://doi.org/10.48550/arXiv.2007.01852

Ferrara, E., & Yang, Z. (2015). Measuring emotional contagion in social media. *PLOS ONE*, *10*(11), e0142390. https://doi.org/10.1371/journal.pone.0142390

Ferron, M., & Massa, P. (2011). Collective memory building in Wikipedia: The case of North African uprisings. *WikiSym '11: Proceedings of the 7th International Symposium on Wikis and Open Collaboration*, 10.

Field, A., Bhat, G., & Tsvetkov, Y. (2019). Contextual affective analysis: A case study of people portrayals in online #MeToo stories. *arXiv:1904.04164 [cs]*. Retrieved April 22, 2020, from http://arxiv.org/abs/1904.04164

Flaskerud, J. H. (2019). A shared sexual ethic? *Issues in Mental Health Nursing*, *40*(8), 727–730. https://doi.org/10.1080/01612840.2018.1557302

Florini, S. (2016). Disrupting the past, reframing the present: Websites, alternative histories and petit récits as black nationalist politics. In A. Hajek, C. Lohmeier, & C. Pentzold (Eds.), *Memory in a mediated world: Remembrance and reconstruction* (pp. 113–128). Palgrave Macmillan UK. https://doi.org/10.1057/9781137470126_7

Ford, H., Pietsch, T., & Tall, K. (2023). Gender and the invisibility of care on Wikipedia. *Big Data & Society*, *10*(2), 20539517231210276. https://doi.org/10.1177/20539517231210276

Foster, M. D. (2019). "Use it or lose it": How online activism moderates the protective properties of gender identity for well-being. *Computers in Human Behavior*, *96*, 163–173. https://doi.org/10.1016/j.chb.2018.11.044

Foucault, M. (1972). *Archaeology of knowledge*. Routledge.

Franiuk, R., Seefelt, J. L., Cepress, S. L., & Vandello, J. A. (2008). Prevalence and effects of rape myths in print journalism: The Kobe Bryant case. *Violence Against Women*, *14*(3), 287–309. https://doi.org/10.1177/1077801207313971

Franiuk, R., Seefelt, J. L., & Vandello, J. A. (2008). Prevalence of rape myths in headlines and their effects on attitudes toward rape. *Sex Roles*, *58*(11-12), 790–801. https://doi.org/10.1007/s11199-007-9372-4

Frayssinet, F. (2018). In Latin America "Me Too" doesn't always mean the same thing. *Inter Press Service*. Retrieved August 3, 2020, from https://www.ipsnews.net/2018/03/latin-america-doesnt-always-mean-thing/

Freelon, D., McIlwain, C., & Clark, M. (2018). Quantifying the power and consequences of social media protest. *New Media & Society*, *20*(3), 990–1011. https://doi.org/10.1177/1461444816676646

Freeman, J. (1969). The BITCH Manifesto. https://www.jofreeman.com/joreen/bitch.htm

Freeman, J. (1972). The tyranny of structurelessness. *Berkeley Journal of Sociology*, *17*, 151–164. https://doi.org/10.1353/wsq.2013.0072

Frese, B., Moya, M., & Megías, J. L. (2004). Social perception of rape: How rape myth acceptance modulates the influence of situational factors. *Journal of Interpersonal Violence*, *19*(2), 143–161. https://doi.org/10.1177/0886260503260245

Friedan, B. (1965). *The feminine mystique*. Penguin.

Fu, K.-w., Chan, C.-h., & Chau, M. (2013). Assessing censorship on microblogs in China: Discriminatory keyword analysis and the real-name registration policy. *IEEE Internet Computing*, *17*(3), 42–50. https://doi.org/10.1109/MIC.2013.28

Gallagher, R. J., Stowell, E., Parker, A. G., & Foucault Welles, B. (2019). Reclaiming stigmatized narratives: The networked disclosure landscape of #MeToo. *Proceedings of the ACM on Human-Computer Interaction*, *3*(CSCW), 1–30. https://doi.org/10.1145/3359198

Gallwitz, F., & Kreil, M. (2022). Investigating the validity of Botometer-based social bot studies. In F. Spezzano, A. Amaral, D. Ceolin, L. Fazio, & E. Serra (Eds.), *Disinformation in Open Online Media* (pp. 63–78). Springer International Publishing. https://doi.org/10.1007/978-3-031-18253-2_5

Gamson, W. (1990). *The strategy of social protest*. Wadsworth.

Gamson, W., & Meyer, D. S. (1996, January). Framing political opportunity. In D. McAdam, J. D. McCarthy, & M. N. Zald (Eds.), *Comparative perspectives on social movements* (1st ed., pp. 275–290). Cambridge University Press. https://doi.org/10.1017/CBO9780511803987.014

Gamson, W., & Modigliani, A. (1989). Media discourse and public opinion on nuclear power: A constructionist approach. *American Journal of Sociology*, *95*(1), 1–37. https://doi.org/10.1086/229213

Gay, R. (2018). *Not That Bad: Dispatches From Rape Culture*. Retrieved April 21, 2020, from https://ebookcentral.proquest.com/lib/qut/detail.action?docID=5432955
OCLC: 1102638819.

Gerbaudo, P. (2012). *Tweets and the streets: Social media and contemporary activism*. Pluto.

Gerbaudo, P. (2017). Social media teams as digital vanguards: The question of leadership in the management of key Facebook and Twitter accounts of Occupy Wall Street, Indignados and UK Uncut. *Information, Communication & Society*, *20*(2), 185–202. https://doi.org/10.1080/1369118X.2016.1161817

Gitlin, T. (1980). *The whole world is watching: Mass media in the making & unmaking of the New Left*. University of California Press.

Giugni, M. (1998). The other side of the coin: Explaining crossnational similarities between social movements. *Mobilization: An International Quarterly*, *3*(1), 89–105. https://doi.org/10.17813/maiq.3.1.l7k0404ru67180t6

Giugni, M., McAdam, D., & Tilly, C. (Eds.). (1998). *How social movements matter*. University of Minnesota Press.

Givan, R. K., Roberts, K. M., & Soule, S. A. (Eds.). (2010). *The diffusion of social movements: Actors, mechanisms, and political effects*. Cambridge University Press. https://doi.org/10.1017/CBO9780511761638

Goel, S., Anderson, A., Hofman, J., & Watts, D. J. (2016). The structural virality of online diffusion. *Management Science*, *62*(1), 180–196. https://doi.org/10.1287/mnsc.2015.2158

González-Bailón, S., & Wang, N. (2016). Networked discontent: The anatomy of protest campaigns in social media. *Social Networks*, *44*, 95–104. https://doi.org/10.1016/j.socnet.2015.07.003

Google. (2019). Me Too Rising. Retrieved March 29, 2021, from https://metoorising.withgoogle.com

Gould, R. V. (1991). Multiple networks and mobilization in the Paris commune, 1871. *American Sociological Review*, *56*(6), 716. https://doi.org/10.2307/2096251

Gould, R. V. (2003). Why do networks matter? Rationalist and structuralist interpretations. In *Social movements and networks: Relational approaches to collective action* (pp. 233–257). Oxford University Press. https://doi.org/10.1093/0199251789.003.0010

Grabowski, J., & Klein, S. (2023). Wikipedia's intentional distortion of the history of the Holocaust. *The Journal of Holocaust Research*, *37*(2), 133–190. https://doi.org/10.1080/25785648.2023.2168939

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380.

Groggel, A., Kokoris, G., & Journet, S. (2024). Stereotypical victims: Visibility of #MeToo disclosures on Twitter. *Violence Against Women*, 10778012241228288. https://doi.org/10.1177/10778012241228288

Grootendorst, M. (2022, March). BERTopic: Neural topic modeling with a class-based TF-IDF procedure. https://doi.org/10.48550/arXiv.2203.05794

Gunnarsson, L. (2018). "Excuse me, but are you raping me now?" Discourse and experience in (the grey areas of) sexual violence. *NORA - Nordic Journal of Feminist and Gender Research*, *26*(1), 4–18. https://doi.org/10.1080/08038740.2017.1395359

Guo, L., Su, C., Paik, S., Bhatia, V., Akavoor, V. P., Gao, G., Betke, M., & Wijaya, D. (2023). Proposing an open-sourced tool for computational framing analysis of multilingual data. *Digital Journalism*, *11*(2), 276–297. https://doi.org/10.1080/21670811.2022.2031241

Halbwachs, M. (1980). *The collective memory* (1st ed). Harper & Row.

Han, E. L. (2023). GitHub as a collaborative curation platform for memory projects of COVID-19 in China. *Information, Communication & Society*, *26*(2), 340–355. https://doi.org/10.1080/1369118X.2022.2161828

Han, L., & Liu, Y. (2023). #Metoo activism without the #MeToo hashtag: Online debates over entertainment celebrities' sex scandals in China. *Feminist Media Studies*, *0*(0), 1–18. https://doi.org/10.1080/14680777.2023.2219857

Han, S. K. (2009). The other ride of Paul Revere: The brokerage role in the making of the American revolution. *Mobilization*, *14*(2), 143–162.

Haraway, D. (1988). Situated knowledges: The science question in feminism and the privilege of partial perspective. *Feminist Studies*, *14*(3), 575. https://doi.org/10.2307/3178066

Harlow, S., & Guo, L. (2014). Will the revolution be Tweeted or Facebooked? Using digital communication tools in immigrant activism. *Journal of Computer-Mediated Communication*, *19*(3), 463–478. https://doi.org/10.1111/jcc4.12062

Harlow, S., Kilgo, D. K., Salaverría, R., & García-Perdomo, V. (2020). Is the whole world watching? Building a typology of protest coverage on social media from around the world. *Journalism Studies*, *21*(11), 1590–1608. https://doi.org/10.1080/1461670X.2020.1776144

Harlow, S., Salaverría, R., Kilgo, D. K., & García-Perdomo, V. (2017). Protest paradigm in multimedia: Social media sharing of coverage about the crime of ayotzinapa, Mexico. *Journal of Communication*, *67*(3), 328–349. https://doi.org/10.1111/jcom.12296

Harrington, C. (2018). Feminist killjoys and women scorned: An analysis of news and commentary on the sexual violence allegations against Julian Assange. *Feminist Criminology*, *13*(1), 87–111. https://doi.org/10.1177/1557085116646194

Harrington, C., & Gerrard, M. (2023, August). Telling an authentic, relatable #MeToo story on YouTube. In K. Boyle & S. Berridge (Eds.), *The Routledge Companion to Gender, Media and Violence* (1st ed., pp. 213–221). Routledge. https://doi.org/10.4324/9781003200871

Harvey, A. C. (2009). *Forecasting, structural time series models and the Kalman filter* (Transf. to dig. print). Cambridge University Press.

Hase, V., Mahl, D., & Schäfer, M. S. (2023). The "computational turn": An "interdisciplinary turn"? A systematic review of text as data approaches in journalism studies. *Online Media and Global Communication*, *2*(1), 122–143. https://doi.org/10.1515/omgc-2023-0003

Haslanger, S. (1995). Ontology and social construction. *Philosophical Topics*, *23*(2), 95–125.

Hassan, N., Mandal, M. K., Bhuiyan, M., Moitra, A., & Ahmed, S. I. (2019a). Can women break the glass ceiling? An analysis of #MeToo hashtagged posts on twitter. *Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, 653–656. https://doi.org/10.1145/3341161.3343701

Hassan, N., Mandal, M. K., Bhuiyan, M., Moitra, A., & Ahmed, S. I. (2019b). Nonparticipation of Bangladeshi women in #MeToo movement. *Proceedings of the Tenth International Conference on Information and Communication Technologies and Development - ICTDX '19*, 1–5. https://doi.org/10.1145/3287098.3287125

Hasunuma, L., & Shin, K.-y. (2019). #MeToo in Japan and South Korea: #WeToo, #WithYou (N. E. Brown, Ed.). *Journal of Women, Politics & Policy*, *40*(1), 97–111. https://doi.org/10.1201/9781003014508-6

Heberle, R. J., & Grace, V. (2009). Theorizing sexual violence. In R. J. Heberle & V. Grace (Eds.), *Introduction: Theorizing sexual violence: Subjectivity and politics in late modernity*. Routledge.

Henn, T., & Posegga, O. (2023). Attention-grabbing news coverage: Violent images of the Black Lives Matter movement and how they attract user attention on Reddit (F. Saracco, Ed.). *PLOS ONE*, *18*(8), e0288962. https://doi.org/10.1371/journal.pone.0288962

Hilbert, M., Barnett, G., & Blumenstock, J. (2019). Computational communication science: A methodological catalyzer for a maturing discipline. *International Journal of Communication*, *13*, 3912–3934.

Himelein-Wachowiak, M., Giorgi, S., Devoto, A., Rahman, M., Ungar, L., Schwartz, H. A., Epstein, D. H., Leggio, L., & Curtis, B. (2021). Bots and misinformation spread on social media: Implications for COVID-19. *Journal of Medical Internet Research*, *23*(5), e26933. https://doi.org/10.2196/26933

Hindes, S., & Fileborn, B. (2019). "Girl power gone wrong": #MeToo, Aziz Ansari, and media reporting of (grey area) sexual violence. *Feminist Media Studies*, *20*(5), 639–656. https://doi.org/10.1080/14680777.2019.1606843

Hollings, J. (2020). It does become personal: Lessons from a news organisation's #MeToo campaign. *Journalism Practice*, *14*(2), 225–239. https://doi.org/10.1080/17512786.2020.1712223

Honnibal, M., Montani, I., Van Landeghem, S., & Boyd, A. (2023, October). spaCy: Industrial-strength natural language processing in Python. Retrieved April 11, 2024, from https://zenodo.org/doi/10.5281/zenodo.1212303

Horeck, T. (2014). #AskThicke: "Blurred Lines," rape Culture, and the feminist hashtag takeover. *Feminist Media Studies*, *14*(6), 1105–1107. https://doi.org/10.1080/14680777.2014.975450

Horeck, T. (2023, August). Sexual violence and social justice: The celebrity #MeToo documentary in the US. In K. Boyle & S. Berridge (Eds.), *The Routledge companion to gender, media and violence* (1st ed., pp. 232–241). Routledge. https://doi.org/10.4324/9781003200871

Horne, B. D., & Adali, S. (2018, May). An exploration of verbatim content republishing by news producers. https://doi.org/10.48550/arXiv.1805.05939

Hoskins, A. (2011). 7/7 and connective memory: Interactional trajectories of remembering in post-scarcity culture. *Memory Studies*, *4*(3), 269–280. https://doi.org/10.1177/1750698011402570

Hoskins, A. (2018a). Memory of the multitude: The end of collective memory. In A. Hoskins (Ed.), *Digital memory studies: Media pasts in transition* (pp. 85–109). Routledge.

Hoskins, A. (2018b). The restless past: An introduction to digital memory and media. In A. Hoskins (Ed.), *Digital memory studies: Media pasts in transition* (pp. 1–24). Routledge.

Howard, P. N., & Hussain, M. M. (2013). *Democracy's fourth wave? Digital media and the Arab Spring*. Oxford University Press.

Iacopini, I., Petri, G., Barrat, A., & Latora, V. (2019). Simplicial models of social contagion. *Nature Communications*, *10*(1), 2485. https://doi.org/10.1038/s41467-019-10431-6

Jackson, J. C., Rand, D., Lewis, K., Norton, M. I., & Gray, K. (2017). Agent-based modeling: A guide for social psychologists. *Social Psychological and Personality Science*, *8*(4), 387–395. https://doi.org/10.1177/1948550617691100

Jackson, S. J., Bailey, M., & Foucault Welles, B. (2019). Women tweet on violence: From #YesAllWomen to #MeToo. *Ada: A Journal of Gender, New media, and Technology*, *15*.

Jackson, S. J., Bailey, M., & Foucault Welles, B. (2020). *#HashtagActivism: Networks of race and gender justice*. MIT Press.

Jackson, S. J., & Foucault Welles, B. (2016). #Ferguson is everywhere: Initiators in emerging counterpublic networks. *Information, Communication & Society*, *19*(3), 397–418. https://doi.org/10.1080/1369118X.2015.1106571

Jankowski, S. (2023). The Wikipedia imaginaire: A new media history beyond Wikipedia.org (2001–2022). *Internet Histories*, *7*(4), 333–353. https://doi.org/10.1080/24701475.2023.2246261

Jansen, R. S. (2007). Resurrection and appropriation: Reputational trajectories, memory work, and the political use of historical figures. *American Journal of Sociology*, *112*(4), 953–1007. https://doi.org/10.1086/508789

Jasper, J. M., & Poulsen, J. D. (1995). Recruiting strangers and friends: Moral shocks and social networks in animal rights and anti-nuclear protests. *Social Problems*, *42*(4), 493–512. https://doi.org/10.2307/3097043

Jeong, E. (2020). *Troll feminism: The rise of popular feminism in South Korea* [Doctoral dissertation, University of York].

Johnson, E. K. (2017). Erasing the scarlet letter: How positive media messages about sex can lead to better sexual health among college men and women. *American Journal of Sexuality Education*, *12*(1), 55–71. https://doi.org/10.1080/15546128.2016.1266456

Johnson, J., Douze, M., & Jégou, H. (2019). Billion-scale similarity search with GPUs. *IEEE Transactions on Big Data*, *7*(3), 535–547.

Joseph, K., Gallagher, R. J., & Foucault Welles, B. (2020, February). *Who says what with whom: Using bi-spectral clustering to organize and analyze social media protest networks* (Preprint). SocArXiv. https://doi.org/10.31235/osf.io/qjcgk

Jungherr, A., Rivero, G., & Gayo-Avello, D. (2020, June). The rise of digital media and the retooling of politics. In *Retooling politics: How digital media are shaping democracy* (1st ed., pp. 1–29). Cambridge University Press. https://doi.org/10.1017/9781108297820

Kansteiner, W. (2002). Finding meaning in memory: A methodological critique of collective memory studies. *History and Theory*, *41*(2), 179–197. https://doi.org/10.1111/0018-2656.00198

Kantor, J., & Twohey, M. (2022). How to measure the impact of #MeToo? *The New York Times*. Retrieved October 4, 2022, from https://www.nytimes.com/interactive/2022/10/03/us/me-too-five-years.html

Karpf, D. (2014). Comment on 'Organization in the crowd: Peer production in large-scale networked protests'. *Information, Communication & Society*, *17*(2), 261–263. https://doi.org/10.1080/1369118X.2013.868020

Katriel, T., & Gutman, Y. (2015). The wall must fall: Memory activism, documentary filmmaking and the second intifada. In A. Reading & T. Katriel (Eds.), *Cultural Memories of Nonviolent Struggles* (pp. 205–225). Palgrave Macmillan UK. https://doi.org/10.1057/9781137032720_11

Keller, J., Mendes, K., & Ringrose, J. (2018). Speaking 'unspeakable things': Documenting digital feminist responses to rape culture. *Journal of Gender Studies*, *27*(1), 22–36. https://doi.org/10.1080/09589236.2016.1211511

Kelly, L. (1987). The continuum of sexual violence. In J. Hanmer & M. Maynard (Eds.), *Women, violence and social control* (pp. 46–60). MacMillan. https://doi.org/10.1177/1557085112442979

Keplinger, K., Johnson, S. K., Kirk, J. F., & Barnes, L. Y. (2019). Women at work: Changes in sexual harassment between September 2016 and September 2018 (V. Capraro, Ed.). *PLOS ONE*, *14*(7), e0218313. https://doi.org/10.1371/journal.pone.0218313

Kesselman, A., Booth, H., Rothstein, V., & Weisstein, N. (2007). Our gang of four: Friendships and women's liberation. In R. B. DuPlessis (Ed.), *The feminist memoir project: Voices from women's liberation* (pp. 25–53). Rutgers University Press.

Khatua, A., Cambria, E., & Khatua, A. (2018). Sounds of silence breakers: Exploring sexual violence on Twitter. *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, 397–400. https://doi.org/10.1109/ASONAM.2018.8508576

Kim, J. H. (2019). Direct democracy and women's political engagement. *American Journal of Political Science*, *63*(3), 594–610. https://doi.org/10.1111/ajps.12420

Kitschelt, H. P. (1986). Political opportunity structures and political protest: Anti-nuclear movements in four democracies. *British Journal of Political Science*, *16*(1), 57–85.

Kitzinger, J. (2004). Media coverage of sexual violence against women and children. In K. Ross & C. Byerly (Eds.), *Women and Media: International Perspectives* (pp. 13–38). Blackwell Publishing.

Kitzinger, J. (2009). Rape in the media. In M. Horvath & J. Brown (Eds.), *Rape* (pp. 74–98). WIllan Publishing.

Koo, J. (2020). South Korean cyberfeminism and trolling: The limitation of online feminist community Womad as counterpublic. *Feminist Media Studies*, *20*(6), 831–846. https://doi.org/10.1080/14680777.2019.1622585

Koopmans, R. (2004). Movements and media: Selection processes and evolutionary dynamics in the public sphere. *Theory and Society*, *33*(3/4), 367–391. https://doi.org/10.1023/B:RYSO.0000038603.34963.de

Koopmans, R. (2007). Protest in time and space: The evolution of waves of contention. In D. A. Snow, S. A. Soule, & H. Kriesi (Eds.), *The Blackwell companion to social movements* (pp. 19–46). Blackwell Publishing Ltd. https://doi.org/10.1002/9780470999103.ch2

Kornhauser, W. (1968). *The Politics of Mass Society*. Routledge.

Kubal, T., & Becerra, R. (2014). Social movements and collective memory: Movements and memory. *Sociology Compass*, *8*(6), 865–875. https://doi.org/10.1111/soc4.12166

Kudugunta, S., & Ferrara, E. (2018). Deep neural networks for bot detection. *Information Sciences*, *467*, 312–322. https://doi.org/10.1016/j.ins.2018.08.019

Kuper, S. (2021). France's #MeToo moment. *Financial Times*. Retrieved March 24, 2024, from https://www.ft.com/content/6c95a1c0-7aa9-4303-9191-75415a94843d

Lanier, C. A. (2001). Rape-accepting attitudes: Precursors to or consequences of forced sex. *Violence Against Women*, *7*(8), 876–885. https://doi.org/10.1177/10778010122182802

Larsen, C. (2018). #MeToo in South Korea: A comparative analysis of feminist perspectives in a cultural context. *International Journal of Foreign Studies*, *11*(2), 39–59. https://doi.org/10.18327/ijfs.2018.12.11.39

Lee, J., & Jeong, E. (2021). The 4B movement: Envisioning a feminist future with/in a non-reproductive future in Korea. *Journal of Gender Studies*, *30*(5), 633–644. https://doi.org/10.1080/09589236.2021.1929097

Lee, J. (2020). Newspaper coverage of sexual assaults in South Korea:Before and after #MeToo movement. *The International Conference on Future of Women*, 1–11. https://doi.org/10.17501/26028646.2020.3101

Lee, M., & Murdie, A. (2021). The global diffusion of the #MeToo movement. *Politics & Gender*, *17*(4), 827–855. https://doi.org/10.1017/S1743923X20000148

Lemmerich, F., Sáez-Trumper, D., West, R., & Zia, L. (2019). Why the world reads Wikipedia: Beyond English speakers. *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*, 618–626. https://doi.org/10.1145/3289600.3291021

Lerner, M. J. (1980). *The belief in a just world: A fundamental delusion*. Plenum.

Levey, C. (2020). Archiving the repertoire, performing the archive: Virtual iterations of second-generation activism in post-dictatorship Argentina. In S. Merrill, E. Keightley, & P. Daphi (Eds.), *Social movements, cultural memory and digital media* (pp. 199–223). Springer International Publishing. https://doi.org/10.1007/978-3-030-32827-6_8

Levy, R., & Mattsson, M. (2020). The effects of social movements: Evidence from #MeToo. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3496903

Liao, S., & Luqiu, L. R. (2022). #MeToo in China: The dynamic of digital activism against sexual assault and harassment in higher education. *Signs: Journal of Women in Culture and Society*, *47*(3), 741–764. https://doi.org/10.1086/717712

Lin, Z., & Yang, L. (2019). 'Me too!': Individual empowerment of disabled women in the #MeToo movement in China. *Disability & Society*, *34*(5), 842–847. https://doi.org/10.1080/09687599.2019.1596608

Littleton, C. (2021, January). Why TikTok's popularity exploded during the pandemic. Retrieved March 14, 2024, from https://variety.com/2021/digital/news/tiktok-popularity-covid-1234893740/

Liu, M. (2023). #Metoo in China: Visceral accounts of rape culture, a non-domestic feminist counterpublic, and networked solidarity. *Feminist Media Studies*, *0*(0), 1–16. https://doi.org/10.1080/14680777.2023.2285718

Loney-Howes, R., Mendes, K., Fernández Romero, D., Fileborn, B., & Núñez Puente, S. (2021). Digital footprints of #MeToo. *Feminist Media Studies*, 1–18. https://doi.org/10.1080/14680777.2021.1886142

Lonsway, K. A., & Fitzgerald, L. F. (1994). Rape myths: In review. *Psychology of Women Quarterly*, *18*(2), 133–164. https://doi.org/10.1111/j.1471-6402.1994.tb00448.x

Lopez, I., Quillivic, R., Evans, H., & Arriaga, R. I. (2019). Denouncing sexual violence: A cross-language and cross-cultural analysis of #MeToo and #BalanceTonPorc. In D. Lamas, F. Loizides, L. Nacke, H. Petrie, M. Winckler, & P. Zaphiris (Eds.), *Human-Computer Interaction – INTERACT 2019* (pp. 733–743, Vol. 11747). Springer International Publishing. https://doi.org/10.1007/978-3-030-29384-0_44

Lowenthal, D. (2012). The past made present. *Historically Speaking*, *13*(4), 2–6. https://doi.org/10.1353/hsp.2012.0040

Lucy, L., Tadimeti, D., & Bamman, D. (2022, October). Discovering differences in the representation of people using contextualized semantic axes. Retrieved November 7, 2022, from http://arxiv.org/abs/2210.12170

Lukose, R. (2018). Decolonizing feminism in the #MeToo era. *The Cambridge Journal of Anthropology*, *36*(2), 34–52. https://doi.org/10.3167/cja.2018.360205

Luyt, B. (2016). Wikipedia, collective memory, and the Vietnam war. *Journal of the Association for Information Science and Technology*, *67*(8), 1956–1961. https://doi.org/10.1002/asi.23518

Makin, D. A., & Morczek, A. L. (2015). The dark side of internet searches: A macro level assessment of rape culture. *International Journal of Cyber Criminology*, *9*, 1–23. https://doi.org/10.5281/ZENODO.22057

Manikonda, L., Beigi, G., Liu, H., & Kambhampati, S. (2018). Twitter for sparking a movement, reddit for sharing the moment: #Metoo through the lens of social media. Retrieved October 21, 2018, from http://arxiv.org/abs/1803.08022

Maquin, L. (2020, April). Personal Interview.

Margetts, H., John, P., Hale, S. A., & Yasseri, T. (2016). *Political turbulence: How social media shape collective action*. Princeton University Press.

Martini, F. (2020). Wer ist #MeToo? Eine netzwerkanalytische Untersuchung (anti-)feministischen Protests auf Twitter. *Medien & Kommunikationswissenschaft*, *68*(3), 255–272. https://doi.org/10.5771/1615-634X-2020-3-255

Massanari, A. (2017). #Gamergate and the Fappening: How Reddit's algorithm, governance, and culture support toxic technocultures. *New Media & Society*, *19*(3), 329–346. https://doi.org/10.1177/1461444815608807

Matthes, J., & Kohring, M. (2008). The content analysis of media frames: Toward improving reliability and validity. *Journal of Communication*, *58*(2), 258–279. https://doi.org/10.1111/j.1460-2466.2008.00384.x

Mazza, M., Cresci, S., Avvenuti, M., Quattrociocchi, W., & Tesconi, M. (2019). RTbust: Exploiting temporal patterns for botnet detection on Twitter. *Proceedings of the 10th ACM Conference on Web Science*, 183–192. https://doi.org/10.1145/3292522.3326015

McAdam, D. (1995). "Initiator" and "Spin-off" movements: Diffusion processes in protest cycles. In M. Traugott (Ed.), *Repertoires and Cycles of Collective Action* (pp. 217–40). Duke Univ. Press.

McAdam, D., & Rucht, D. (1993). The cross-national diffusion of movement ideas. *The ANNALS of the American Academy of Political and Social Science*, *528*(1), 56–74. https://doi.org/10.1177/0002716293528001005

McAdam, D., Tarrow, S., & Tilly, C. (2001). *Dynamics of contention*. Cambridge University Press.

McCarthy, J. D., & Zald, M. N. (1977). Resource mobilization and social movements: A partial theory. *American Journal of Sociology*, *82*(6), 1212–1241. https://doi.org/10.1086/226464

McCurdy, P. (2012). Social movements, protest and mainstream media: Aocial movements & mainstream media. *Sociology Compass*, *6*(3), 244–255. https://doi.org/10.1111/j.1751-9020.2011.00448.x

McLeod, D. M., & Hertog, J. K. (1992). The manufacture of 'public opinion' by reporters: Informal cues for public perceptions of protest groups. *Discourse & Society*, *3*(3), 259–275. https://doi.org/10.1177/0957926592003003001

Melucci, A. (1989). *Nomads of the present*. Hutchinson Radius.

Melucci, A. (1996). *Challenging codes collective action in the information age*. Cambridge University Press.

Mendes, K. (2015). *Slutwalk: Feminism, activism and media*. Palgrave Macmillan.

Mendes, K., & Jeong, E. (2023, August). Digital feminist activism against gender violence in South Korea. In K. Boyle & S. Berridge (Eds.), *The Routledge companion to gender, media and violence* (1st ed., pp. 543–552). Routledge. https://doi.org/10.4324/9781003200871

Mendes, K., Ringrose, J., & Keller, J. (2018). #MeToo and the promise and pitfalls of challenging rape culture through digital feminist activism. *European Journal of Women's Studies*, *25*(2), 236–246. https://doi.org/10.1177/1350506818765318

Mendes, K., Ringrose, J., & Keller, J. (2019). *Digital feminist activism: Girls and women fight back against rape culture*. Oxford University Press. https://doi.org/10.1093/oso/9780190697846.001.0001

Merrill, S., Keightley, E., & Daphi, P. (Eds.). (2020). *Social Movements, Cultural Memory and Digital Media: Mobilising Mediated Remembrance*. Springer International Publishing. https://doi.org/10.1007/978-3-030-32827-6

Merrill, S., & Lindgren, S. (2020). The rhythms of social movement memories: The mobilization of Silvio Meier's activist remembrance across platforms. *Social Movement Studies*, *19*(5-6), 657–674. https://doi.org/10.1080/14742837.2018.1534680

MeToo movement. (2024). *Wikipedia*. Retrieved March 16, 2024, from https://en.wikipedia.org/w/index.php?title=MeToo_movement&oldid=1212399689

#MeToo Project Schlesinger Library. (n.d.). Collection goal & scope statement. Retrieved March 5, 2024, from https://www.schlesinger-metooproject-radcliffe.org/collection

Meyer, D. S. (2004). Protest and political opportunities. *Annual Review of Sociology*, *30*(1), 125–145. https://doi.org/10.1146/annurev.soc.30.012703.110545

Meyer, D. S., & Whittier, N. (1994). Social movement spillover. *Social Problems*, *41*(2), 277. Retrieved December 15, 2018, from https://about.jstor.org/terms

Milano, A. (2017, October). Tweet. Retrieved April 29, 2020, from https://twitter.com/Alyssa_Milano/status/919659438700670976

Miura, M. (2021). Flowers for sexual assault victims: Collective empowerment through empathy in Japan's #MeToo movement. *Politics & Gender*, *17*(4), 521–527. https://doi.org/10.1017/S1743923X21000258

Mizoroki, S., Shifman, L., & Hayashi, K. (2023). Hashtag activism found in translation: Unpacking the reformulation of #MeToo in Japan. *New Media & Society*, 146144482311535. https://doi.org/10.1177/14614448231153571

Møller, A. G., Dalsgaard, J. A., Pera, A., & Aiello, L. M. (2023, April). Is a prompt and a few samples all you need? Using GPT-4 for data augmentation in low-resource classification tasks. Retrieved May 3, 2023, from http://arxiv.org/abs/2304.13861

Mønsted, B., Sapieżyński, P., Ferrara, E., & Lehmann, S. (2017). Evidence of complex contagion of information in social media: An experiment using Twitter bots. *PLoS ONE*, *12*(7), e0184148. https://doi.org/10.1371/journal.pone.0184148

Moorti, S. (2002). *Color of rape: Gender and race in television's public spheres*. State University of New York Press.

Moricz, S. (2019). Using artificial intelligence to recapture norms: Did #MeToo change gender norms in Sweden? *arXiv:1903.00690 [econ, q-fin]*. Retrieved September 14, 2020, from http://arxiv.org/abs/1903.00690

Mortimer, S., Powell, A., & Sandy, L. (2019). 'Typical scripts' and their silences: Exploring myths about sexual violence and LGBTQ people from the perspectives of support workers. *Current Issues in Criminal Justice*, *31*(3), 333–348. https://doi.org/10.1080/10345329.2019.1639287

Mueller, A., Wood-Doughty, Z., Amir, S., Dredze, M., & Nobles, A. L. (2021). Demographic representation and collective storytelling in th Me Too Twitter hashtag activism movement. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW1), 1–28. https://doi.org/10.1145/3449181

Muhlmeyer, M., Huang, J., & Agarwal, S. (2019). Event triggered social media chatter: A new modeling framework. *IEEE Transactions on Computational Social Systems*, *6*(2), 197–207. https://doi.org/10.1109/TCSS.2019.2897674

Mukherjee, I., Shah, P. V., & Dexter, T. E. (2023). "Feminism in India" framing #MeTooIndia: A case of digital activism. In C. Wiesslitz (Ed.), *Women's activism online and the global struggle for social change* (pp. 277–299). Springer International Publishing. https://doi.org/10.1007/978-3-031-31621-0_14

Nelon, J. L., Spadine, M. N., Patterson, M. S., Brown, S. E., Bookout, C. L., Woods, L. M., & Fehr, S. K. (2021). An observational analysis of 'Me Too' narratives from YouTube. *Health Behavior Research*, *4*(2). https://doi.org/10.4148/2572-1836.1088

Nicholls, T., & Culpepper, P. D. (2020). Computational identification of media frames: Strengths, weaknesses, and opportunities. *Political Communication*, 1–23. https://doi.org/10.1080/10584609.2020.1812777

Nutbeam, M., & Mereish, E. H. (2022). Negative attitudes and beliefs toward the #MeToo movement on Twitter. *Journal of Interpersonal Violence*, *37*(15-16), NP13018–NP13044. https://doi.org/10.1177/08862605211001470

O'Hara, S. (2012). Monsters, playboys, virgins and whores: Rape myths in the news media's coverage of sexual violence. *Language and Literature: International Journal of Stylistics*, *21*(3), 247–259. https://doi.org/10.1177/0963947012444217

Olick, J. K. (1999). Collective memory: The two cultures. *Sociological Theory*, *17*(3), 333–348. https://doi.org/10.1111/0735-2751.00083

Olson, M. (1965). *The logic of collective action: Public goods and the theory of groups*. Harvard University Press.

Orgad, S., & Gill, R. (2019). Safety valves for mediated female rage in the #MeToo era. *Feminist Media Studies*, *19*(4), 596–603. https://doi.org/10.1080/14680777.2019.1609198

Osborne, C., Graham, M., & Dittus, M. (2020). Edit wars in a contested digital city: Mapping Wikipedia's uneven augmentations of berlin.

Palmer-Mehta, V. (2018). The subversive power of survivor rhetoric: An innovative archive of survivor discourse in *New York Magazine*. *Women's Studies in Communication*, *41*(2), 159–182. https://doi.org/10.1080/07491409.2018.1471764

Pandey, R., Purohit, H., Stabile, B., & Grant, A. (2018). Distributional semantics approach to detect intent in Twitter conversations on sexual assaults. *arXiv:1810.01012 [cs]*. Retrieved July 13, 2020, from http://arxiv.org/abs/1810.01012

Park, A. (2017). #MeToo reaches 85 countries with 1.7M tweets. *CBS News*. Retrieved February 2, 2022, from https://www.cbsnews.com/news/metoo-reaches-85-countries-with-1-7-million-tweets/

Park, S. (2024). #MeToo movement in Korean arts & culture sector and gender mainstreaming strategies in cultural policy. *International Journal of Cultural Policy*, *0*(0), 1–16. https://doi.org/10.1080/10286632.2024.2306132

Pastor-Satorras, R., Castellano, C., Van Mieghem, P., & Vespignani, A. (2015). Epidemic processes in complex networks. *Reviews of Modern Physics*, *87*(3), 925–979. https://doi.org/10.1103/RevModPhys.87.925

Pemstein, D., Marquardt, K. L., Tzelgov, E., Wang, Y.-t., Medzihorsky, J., Krusell, J., Miri, F., & von Römer, J. (2023). The V-dem measurement model: Latent variable analysis for cross-national and cross-temporal expert-coded data. *Varieties of Democracy Institute Working Paper*, *21*(8th Ed). https://v-dem.net/wp.html

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). The development and psychometric properties of LIWC2015.

Penney, J., & Dadas, C. (2014). (Re)Tweeting in the service of protest: Digital composition and circulation in the Occupy Wall Street movement. *New Media & Society*, *16*(1), 74–90. https://doi.org/10.1177/1461444813479593

Pentzold, C. (2009). Fixing the floating gap: The online encyclopaedia Wikipedia as a global memory place. *Memory Studies*, *2*(2), 255–272. https://doi.org/10.1177/1750698008102055

Phipps, A. (2021). White tears, white rage: Victimhood and (as) violence in mainstream feminism. *European Journal of Cultural Studies*, *24*(1), 81–93. https://doi.org/10.1177/1367549420985852

Piolat, A., Booth, R., Chung, C., Davids, M., & Pennebaker, J. (2011). La version française du dictionnaire pour le LIWC : modalités de construction et exemples d'utilisation. *Psychologie Française*, *56*(3), 145–159. https://doi.org/10.1016/j.psfr.2011.07.002

Piven, F. F., & Cloward, R. A. (1979). *Poor people's movements: Why they succeed, how they fail*. Pantheon Books.

Poell, T., Abdulla, R., Rieder, B., Woltering, R., & Zack, L. (2016). Protest leadership in the age of social media. *Information, Communication & Society*, *19*(7), 994–1014. https://doi.org/10.1080/1369118X.2015.1088049

Polletta, F. (2006). *It was like a fever: Storytelling in protest and politics*. University of Chicago Press.

Rashkin, H., Singh, S., & Choi, Y. (2016). Connotation frames: A data-driven investigation. *arXiv:1506.02739 [cs]*. Retrieved May 1, 2020, from http://arxiv.org/abs/1506.02739

Reestorff, C. M. (2021). The affective politics of interfacial news: Danish news media's coverage of #MeToo on Facebook. In B. M. S. Thomsen (Ed.), *Affects, interfaces, events* (pp. 122–146). Imbricate! Press.

Retrieved June 17, 2021, from http://imbricate.press/book/affects-interfaces-events/the-affective-politics-of-interfacial-news-danish-new-medias-coverage-of-metoo-on-facebook/

Reyes-Menendez, A., Saura, J. R., & Thomas, S. B. (2020). Exploring key indicators of social identity in the #MeToo era: Using discourse analysis in UGC. *International Journal of Information Management*, *54*, 102129. https://doi.org/10.1016/j.ijinfomgt.2020.102129

Rho, E. H. R., Mark, G., & Mazmanian, M. (2018). Fostering civil discourse online: Linguistic behavior in comments of #MeToo articles across political perspectives. *Proceedings of the ACM on Human-Computer Interaction*, *2*(CSCW), 1–28. https://doi.org/10.1145/3274416

Rieder, B. (2015). Introducing the YouTube data tools. Retrieved March 14, 2024, from http://thepoliticsofsystems.net/2015/05/exploring-youtube/

Roberts, H., Bhargava, R., Valiukas, L., Jen, D., Malik, M. M., Bishop, C. S., Ndulue, E. B., Dave, A., Clark, J., Etling, B., Faris, R., Shah, A., Rubinovitz, J., Hope, A., D'Ignazio, C., Bermejo, F., Benkler, Y., & Zuckerman, E. (2021). Media cloud: Massive open source collection of global news on the open web. *Proceedings of the International AAAI Conference on Web and Social Media*, *15*(1), 1034–1045. https://doi.org/10.1609/icwsm.v15i1.18127

Robinson, A. B. a. J. (2023). Chess world splits over handling of sexual misconduct allegations. *WSJ*. Retrieved August 18, 2023, from https://www.wsj.com/sports/chess-allegations-st-louis-club-3393030e

Roggeband, C. (2010). Transnational networks and institutions: How diffusion shaped the politicization of sexual harassment in Europe. In R. K. Givan, K. M. Roberts, & S. Soule (Eds.), *The diffusion of social movements: Actors, mechanisms, and political effects* (pp. 19–33). Cambridge Univerity Press.

Rose, G. (2001). *Visual methodologies: An introduction to the interpretation of visual materials*. Sage.

Rucht, D. (2004). The quadruple 'A': Media strategies of protest movements since the 1960s. In W. V. D. Donk, B. D. Loader, P. G. Nixon, & D. Rucht (Eds.), *Cyberprotest: New media, citizens and social movements* (pp. 42–65). Routledge.

Santia, G. C., Mujib, M. I., & Williams, J. R. (2019). Detecting social bots on Facebook in an information veracity context. *Proceedings of the International AAAI Conference on Web and Social Media*, *13*, 463–472. https://doi.org/10.1609/icwsm.v13i01.3244

Sap, M., Prasettio, M. C., Holtzman, A., Rashkin, H., & Choi, Y. (2017). Connotation frames of power and agency in modern films. *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, 2329–2334. https://doi.org/10.18653/v1/D17-1247

Schelling, T. C. (1971). Dynamic models of segregation. *The Journal of Mathematical Sociology*, *1*(2), 143–186. https://doi.org/10.1080/0022250X.1971.9989794

Schwarz, C. G. (2023, March). On its 20th anniversary, my testimonial on the Harvard STS Program. Retrieved March 14, 2024, from https://medium.com/@claudia_gertraud/on-its-20th-anniversary-my-testimonial-on-the-harvard-sts-program-64100f6caac7

Searle, J. R. (1980). Minds, brains, and programs. *Behavioral and Brain Sciences*, *3*(3), 417–424. https://doi.org/10.1017/S0140525X00005756

Segato, R. L. (2014). Las nuevas formas de la guerra y el cuerpo de las mujeres. *Sociedade e Estado*, *29*(2), 341–371. https://doi.org/10.1590/S0102-69922014000200003

Serisier, T. (2018). *Speaking out: Feminism, rape and narrative politics*. Springer.

Shahin, S., Zheng, P., Sturm, H. A., & Fadnis, D. (2016). Protesting the paradigm: A comparative study of news coverage of protests in Brazil, China, and India. *The International Journal of Press/Politics*, *21*(2), 143–164. https://doi.org/10.1177/1940161216631114

Shao, C., Ciampaglia, G. L., Varol, O., Yang, K.-C., Flammini, A., & Menczer, F. (2018). The spread of low-credibility content by social bots. *Nature Communications*, *9*(1), 4787. https://doi.org/10.1038/s41467-018-06930-7

Sheridan, D. M., Ridolfo, J., & Michel, A. J. (2012). *The available means of persuasion: Mapping a theory and pedagogy of multimodal public rhetoric*. Parlor Press.

Silveirinha, M. J., Simões, R. B., & Santos, T. (2020). Him Too? Cristiano Ronaldo and the news coverage of a rape case allegation. *Journalism Practice*, *14*(2), 208–224. https://doi.org/10.1080/17512786.2019.1693279

Singer, B. D. (1970). Mass media and communication processes in the Detroit riot of 1967. *Public Opinion Quarterly*, *34*(2), 236. https://doi.org/10.1086/267793

Singer, P., Lemmerich, F., West, R., Zia, L., Wulczyn, E., Strohmaier, M., & Leskovec, J. (2017). Why we read Wikipedia. *Proceedings of the 26th International Conference on World Wide Web*, 1591–1600. https://doi.org/10.1145/3038912.3052716

Siuta, R. L., Martin, R. C., Dray, K. K., Liu, S.-N. C., & Bergman, M. E. (2023). Who posted #MeToo, why, and what happened: A mixed methods examination. *Frontiers in Public Health*, *11*, 1060163. https://doi.org/10.3389/fpubh.2023.1060163

SlutWalk. (2024). *Wikipedia*. Retrieved March 16, 2024, from https://en.wikipedia.org/w/index.php?title=SlutWalk&oldid=1213160547

Smit, R., Heinrich, A., & Broersma, M. (2017). Witnessing in the new memory ecology: Memory construction of the Syrian conflict on YouTube. *New Media & Society*, *19*(2), 289–307. https://doi.org/10.1177/1461444815604618

Smit, R., Heinrich, A., & Broersma, M. (2018). Activating the past in the Ferguson protests: Memory work, digital activism and the politics of platforms. *New Media & Society*, *20*(9), 3119–3139. https://doi.org/10.1177/1461444817741849

Snow, D. A., & Benford, R. D. (1992). Master frames and cycles of protest. In C. M. Mueller & A. D. Morris (Eds.), *Frontiers in social movement theory* (pp. 133–155). Yale University Press.

Snow, D. A., Rochford, E. B., Worden, S. K., & Benford, R. D. (1986). Frame alignment processes, micromobilization, and movement participation. *American Sociological Review*, *51*(4), 464. https://doi.org/10.2307/2095581

Snow, D. A., Zurcher, L. A., & Ekland-Olson, S. (1980). Social networks and social movements: A microstructural approach to differential recruitment. *American Sociological Review*, *45*(5), 787–801.

SocioCultural Research Consultants, L. (2021). Dedoose. www.dedoose.com

Song, S. (2023). Digital feminism: In the aftermath of #MeToo, what's next for workplace equity for women? *Journal of Human Rights*, 1–17. https://doi.org/10.1080/14754835.2023.2199025

Soule, S. (1997). The student divestment movement in the united states and tactical diffusion: The shantytown protest. *Social Forces*, *75*(3), 855–882.

Starkey, J. C., Koerber, A., Sternadori, M., & Pitchford, B. (2019). #MeToo goes global: Media framing of silence breakers in four national settings. *Journal of Communication Inquiry*, *43*(4). https://doi.org/10.1177/0196859919865254

Strang, D., & Meyer, J. W. (1993). Institutional conditions for diffusion. *Theory and Society*, *22*(4), 487–511. https://doi.org/10.1007/BF00993595

Stubbs-Richardson, M., Gilbreath, S., Paul, M., & Reid, A. (2023). It's a global #MeToo: A cross-national comparison of social change associated with the movement. *Feminist Media Studies*, 1–20. https://doi.org/10.1080/14680777.2023.2231654

Suk, J., Sun, Y., Sun, L., Li, M., Farías, C., Kwon, H., Ghosh, S., Borah, P., Mini, D. S., Correa, T., Garlough, C., & Shah, D. V. (2023). 'Think global, act local': How #MeToo hybridized across borders and platforms for contextual relevance. *Information, Communication & Society*, 1–22. https://doi.org/10.1080/1369118X.2023.2219716

Sumi, R., Yasseri, T., Rung, A., Kornai, A., & Kertesz, J. (2011). Edit wars in Wikipedia. *2011 IEEE Third Int'l Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third Int'l Conference on Social Computing*, 724–727. https://doi.org/10.1109/PASSAT/SocialCom.2011.47

Tarrow, S. (2005). *The new transnational activism*. Cambridge University Press.

Tarrow, S. (2022). *Power in movement: Social movements and contentious politics* (Revised and updated fourth edition). Cambridge University Press.

Tatz, K. B. G. (2021). *#MeToo: A qualitative approach to understanding a social movement and its impact on survivorhood* [Doctoral dissertation, University of Pennsylvania].

TensorFlow Developers. (2023, November). TensorFlow. https://doi.org/10.5281/ZENODO.4724125

Thompson, A., & Tapp, S. N. (2022, September). *Criminal victimization, 2021* (tech. rep. No. 305101). Bureau of Justice Statistics. https://bjs.ojp.gov/library/publications/criminal-victimization-2021

Tickell, A. (2022). How should complainer anonymity for sexual offences be introduced in Scotland? Learning the international lessons of #LetHerSpeak. *Edinburgh Law Review*, *26*(3), 355–389. https://doi.org/10.3366/elr.2022.0783

Tilly, C. (1977). Getting it together in Burgundy, 1675-1975. *Theory and Society*, *4*(4). https://doi.org/10.1007/BF00187423

Tilly, C. (2008). *Contentious performances*. Cambridge Univerity Press.

Tilly, C., & Tarrow, S. (2015). *Contentious politics* (Second revised edition). Oxford University Press.

Touraine, A. (1977). *The self-production of society*. University of Chicago Press.

Trott, V. (2018). Connected feminists: Foregrounding the interpersonal in connective action. *Australian Journal of Political Science*, *53*(1), 116–129. https://doi.org/10.1080/10361146.2017.1416583

Trott, V. (2019). *Welcome to the coven: Organising feminist activism in the connective era* [Doctoral dissertation, University of Melbourne].

Trott, V. (2020). Networked feminism: Counterpublics and the intersectional issues of #MeToo. *Feminist Media Studies*, 1–18. https://doi.org/10.1080/14680777.2020.1718176

Tsvetkova, M., García-Gavilanes, R., Floridi, L., & Yasseri, T. (2017). Even good bots fight: The case of Wikipedia. *PLOS ONE*, 13.

Tuzcu, P. (2016). "Allow access to location?": Digital feminist geographies. *Feminist Media Studies*, *16*(1), 150–163. https://doi.org/10.1080/14680777.2015.1093153

Twyman, M., Keegan, B. C., & Shaw, A. (2017). Black lives matter in Wikipedia: Collective memory and collaboration around online social movements. *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 1400–1412. https://doi.org/10.1145/2998181.2998232

United Nations Development Programme & United Nations Women. (2023). The paths to equal. *United Nations Development Programme*. https://hdr.undp.org/content/paths-equal

Vasi, I. B., & Suh, C. S. (2016). Online activities, spatial proximity, and the diffusion of the Occupy Wall Street movement in the United States. *Mobilization: An International Quarterly*, *21*(2), 139–154. https://doi.org/10.17813/1086-671X-22-2-139

Vera-Gray, F. (2017). 'Talk about a cunt with too much idle time': Trolling feminist research. *Feminist Review*, *115*(1), 61–78. https://doi.org/10.1057/s41305-017-0038-y

Vu, T. M., Probst, C., Epstein, J. M., Brennan, A., Strong, M., & Purshouse, R. C. (2019). Toward inverse generative social science using multi-objective genetic programming. *Genetic and Evolutionary Computation Conference: [proceedings]. Genetic and Evolutionary Computation Conference*, *2019*, 1356–1363. https://doi.org/10.1145/3321707.3321840

Waiselfisz, J. J. (2015). *Mapa da violência 2015* (tech. rep.). FLASCO. Retrieved April 16, 2024, from https://biblioteca.flacso.org.br/?publication=mapa-da-violencia-2015-homicidio-de-mulheres-no-brasil

Walsh, D. (2020). The 22-year-old force behind Egypt's growing #MeToo movement. *The New York Times*. Retrieved March 30, 2021, from https://www.nytimes.com/2020/10/02/world/middleeast/egypt-metoo-sexual-harassment-ashraf.html

Wang, Y., & Tavmen, G. (2024). New outlets of digital feminist activism in China: The #SeeFemaleWorkers campaign. *Feminist Media Studies*, *0*(0), 1–17. https://doi.org/10.1080/14680777.2024.2334782

Wang, Z., Hale, S., Adelani, D. I., Grabowicz, P., Hartman, T., Flöck, F., & Jurgens, D. (2019). Demographic inference and representative population estimates from multilingual social media data. *The World Wide Web Conference on - WWW '19*, 2056–2067. https://doi.org/10.1145/3308558.3313684

Ward, C. (1988). The attitudes toward rape victims scale: Construction, validation, and cross-cultural applicability. *Psychology of Women Quarterly*, *12*(2), 127–146. https://doi.org/10.1111/j.1471-6402.1988.tb00932.x

Waterhouse-Watson, D. (2016). News media on trial: Towards a feminist ethics of reporting footballer sexual assault trials. *Feminist Media Studies*, *16*(6), 952–967. https://doi.org/10.1080/14680777.2016.1162827

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature*, *393*, 440–442.

Whitlinger, C. (2021). *Between remembrance and repair: Commemorating racial violence in Philadelphia, Mississippi*. The University of North Carolina Press.

Wikipedia:Verifiability. (2024). *Wikipedia*. Retrieved April 2, 2024, from https://en.wikipedia.org/w/index.php?title=Wikipedia:Verifiability&oldid=1213700438

Worthington, N. (2020). Celebrity-bashing or #MeToo contribution? *New York Times Online* readers debate the boundaries of hashtag feminism. *The Communication Review*, *23*(1), 46–65. https://doi.org/10.1080/10714421.2019.1704110

Wu, H. H., Gallagher, R. J., Alshaabi, T., Adams, J. L., Minot, J. R., Arnold, M. V., Welles, B. F., Harp, R., Dodds, P. S., & Danforth, C. M. (2023). Say their names: Resurgence in the collective attention toward Black victims of fatal police violence following the death of George Floyd. *PLOS ONE*, *18*(1), e0279225. https://doi.org/10.1371/journal.pone.0279225

Xiong, Y., Cho, M., & Boatwright, B. (2019). Hashtag activism and message frames among social movement organizations: Semantic network analysis and thematic analysis of Twitter during the #MeToo movement. *Public Relations Review*, *45*(1), 10–23. https://doi.org/10.1016/j.pubrev.2018.10.014

Xu, Z., Jain, S., & Kankanhalli, M. (2024, January). Hallucination is inevitable: An innate limitation of large language models. https://doi.org/10.48550/arXiv.2401.11817

Yang, K.-C., Ferrara, E., & Menczer, F. (2022). Botometer 101: Social bot practicum for computational social scientists. *Journal of Computational Social Science*, *5*(2), 1511–1528. https://doi.org/10.1007/s42001-022-00177-5

Yang, K.-C., Varol, O., Davis, C. A., Ferrara, E., Flammini, A., & Menczer, F. (2019). Arming the public with artificial intelligence to counter social bots. *Human Behavior and Emerging Technologies*, *1*(1), 48–61. https://doi.org/10.1002/hbe2.115

Yang, K.-C., Varol, O., Hui, P.-M., & Menczer, F. (2020). Scalable and generalizable social bot detection through data selection. *Proceedings of the AAAI Conference on Artificial Intelligence*, *34*(01), 1096–1103. https://doi.org/10.1609/aaai.v34i01.5460

Yasseri, T., Spoerri, A., Graham, M., & Kertesz, J. (2013). The most controversial topics in Wikipedia: A multilingual and geographical analysis. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2269392

Yasseri, T., Sumi, R., & Kertész, J. (2012). Circadian patterns of Wikipedia editorial activity: A demographic analysis (A. Szolnoki, Ed.). *PLoS ONE*, *7*(1), e30091. https://doi.org/10.1371/journal.pone.0030091

Yu, X., Daida, S. R., Boy, J., & Hong, L. (2020). The effect of structural affinity on the diffusion of a transnational online movement: The case of #MeToo. In S. Aref, K. Bontcheva, M. Braghieri, F. Dignum, F. Giannotti, F. Grisolia, & D. Pedreschi (Eds.), *Social informatics* (pp. 447–460, Vol. 12467). Springer International Publishing. https://doi.org/10.1007/978-3-030-60975-7_33

Yu, X., Mashhadi, A., Boy, J., Nielsen, R. C., & Hong, L. (2022). Causal impact model to evaluate the diffusion effect of social media campaigns. https://doi.org/10.48340/ECSCW2022_EP10

Zacharek, S., Dockterman, E., & Edwards, H. S. (2017). TIME person of the year 2017: The silence breakers. *Time*. Retrieved April 17, 2020, from https://time.com/time-person-of-the-year-2017-silence-breakers/

Zald, M. N. (1996). Culture, ideology, and strategic framing. In D. McAdam, J. D. McCarthy, & M. N. Zald (Eds.), *Comparative perspectives on social movements: Political opportunities, mobilizing structures, and cultural framings* (pp. 261–274). Cambridge Univerity Press.

Zald, M. N., & McCarthy, J. D. (Eds.). (1987). *Social movements in an organizational society: Collected essays*. Transaction Books.

Zamponi, L. (2013). Collective memory and social movements. In D. A. Snow, D. Della Porta, B. Klandermans, & D. McAdam (Eds.), *The Wiley-Blackwell encyclopedia of social and political movements*. Blackwell Publishing LTD.

Zamponi, L. (2020). #Ioricordo, beyond the Genoa G8: Social practices of memory work and the digital remembrance of contentious pasts in Italy. In S. Merrill, E. Keightley, & P. Daphi (Eds.), *Social movements, cultural memory and digital media* (pp. 141–171). Springer International Publishing. https://doi.org/10.1007/978-3-030-32827-6_6

Zeng, J. (2020). #MeToo as connective action: A study of the anti-sexual violence and anti-sexual harassment campaign on Chinese social media in 2018. *Journalism Practice*, *14*(2), 171–190. https://doi.org/10.1080/17512786.2019.1706622

Zerubavel, E. (1996). Social memories: Steps to a sociology of the past. *Qualitative Sociology*, *19*(3), 283–299. https://doi.org/10.1007/BF02393273

Zheng, X., Han, J., & Sun, A. (2018). A survey of location prediction on Twitter. *IEEE Transactions on Knowledge and Data Engineering*, *30*(9), 1652–1671. https://doi.org/10.1109/TKDE.2018.2807840

Zuckerman, E., Matias, J. N., Bhargava, R., Bermejo, F., & Ko, A. (2019). Whose death matters? A quantitative analysis of media attention to deaths of Black Americans in police confrontations, 2013–2016. *International Journal of Communication*, *13*(0). https://ijoc.org/index.php/ijoc/article/view/8782

Appendices

Appendix A

Article I: Statistical Outputs

This appendix displays a number of example generalized linear regression outputs in the time-aggregated statistical approach in Article I. Details of dependent variables are found in 3.7.1.

Table A.1

Generalized Linear Regression for Period 3: Activity, Forward Step-wise Search

Dep. Variable:	Activity	**No. Observations:**	3139
Model:	GLM	**Df Residuals:**	3137
Model Family:	NegativeBinomial	**Df Model:**	1
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-4803.9
Date:	Thu, 13 Oct 2022	**Deviance:**	4424.7
Time:	17:32:12	**Pearson chi2:**	1.94e+04
No. Iterations:	10	**Pseudo R-squ. (CS):**	0.008211
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	0.3749	0.036	10.320	0.000*	0.304	0.446
Average_Activity_Before_Peak	0.0050	0.001	5.294	0.000*	0.003	0.007

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 3. Dependent variable here is activity. Note that interaction did not appear at all in the final model selected based on a **forward** step-wise search.
$^{*}p < .05$

Table A.2

Generalized Linear Regression for Period 3: Activity, Backward Step-wise Search

Dep. Variable:	Activity	**No. Observations:**	3139
Model:	GLM	**Df Residuals:**	3137
Model Family:	NegativeBinomial	**Df Model:**	1
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-4816.3
Date:	Sun, 20 Feb 2022	**Deviance:**	4449.5
Time:	15:05:17	**Pearson chi2:**	2.17e+04
No. Iterations:	7	**Pseudo R-squ. (CS):**	0.0003460
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	0.4881	0.030	16.175	0.000*	0.429	0.547
org[T.True]	0.1054	0.102	1.034	0.301	-0.094	0.305

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 3. Dependent variable here is activity. Note that interaction did not appear at all in the final model selected based on a **backward** step-wise search. The only nonzero coefficient is whether the account was an organization as inferred by M3 (Z. Wang et al., 2019).
$^{*}p < .05$

Table A.3

Generalized Linear Regression for Period 1: Activity, Step-wise Search

Dep. Variable:	Actvitiy	**No. Observations:**	2726
Model:	GLM	**Df Residuals:**	2724
Model Family:	NegativeBinomial	**Df Model:**	1
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-11287.
Date:	Sun, 20 Feb 2022	**Deviance:**	4587.9
Time:	13:56:09	**Pearson chi2:**	1.39e+04
No. Iterations:	6	**Pseudo R-squ. (CS):**	2.781e-05
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	3.4782	0.030	117.025	0.000*	3.420	3.536
org[T.True]	0.0206	0.075	0.275	0.784	-0.127	0.168

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 1. Dependent variable here is activity. The selected model for period 1 and activity as dependent variable was the same for both forward and backward step-wise searches. The only nonzero coefficient is whether the account was an organization as inferred by M3 (Z. Wang et al., 2019).
$^{*}p < .05$

Table A.4

Generalized Linear Regression for Period 2: Activity, Step-wise Search

Dep. Variable:	Activity	**No. Observations:**	4707
Model:	GLM	**Df Residuals:**	4705
Model Family:	NegativeBinomial	**Df Model:**	1
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-7672.4
Date:	Sun, 20 Feb 2022	**Deviance:**	7110.4
Time:	13:58:05	**Pearson chi2:**	8.24e+04
No. Iterations:	7	**Pseudo R-squ. (CS):**	0.0003151
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	0.6881	0.031	22.002	0.000*	0.627	0.749
gender[T.True]	-0.0566	0.046	-1.219	0.223	-0.148	0.034

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 2. Dependent variable here is activity. The selected model for period 2 and activity as dependent variable was the same for both forward and backward step-wise searches. The only nonzero coefficient is whether the account was an gender as inferred by M3 (Z. Wang et al., 2019).
* $p < .05$

Table A.5

Generalized Linear Regression for Period 1: Interval, Step-wise Search

Dep. Variable:	Interval (Minutes)	**No. Observations:**	220
Model:	GLM	**Df Residuals:**	207
Model Family:	NegativeBinomial	**Df Model:**	12
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-2202.9
Date:	Sun, 20 Feb 2022	**Deviance:**	371.57
Time:	13:56:17	**Pearson chi2:**	342.
No. Iterations:	100	**Pseudo R-squ. (CS):**	0.02276
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	4.4857	0.104	42.976	0.000*	4.281	4.690
lang_diff[T.True]	4.4857	0.104	42.976	0.000*	4.281	4.690
org[T.True]	0.1521	0.263	0.578	0.563	-0.364	0.668
age[T.30-39]	0.5509	0.295	1.868	0.062	-0.027	1.129
age[T.<=18]	0.1594	0.295	0.540	0.589	-0.420	0.738
age[T.>=40]	-0.2069	0.237	-0.873	0.383	-0.671	0.258
gender[T.True]	0.4821	0.198	2.439	0.015*	0.095	0.869
reciprocal	0.0034	0.019	0.177	0.860	-0.034	0.041
act_pre_peak_avg	0.4875	0.328	1.487	0.137	-0.155	1.130
int_pre_peak	0.0015	0.003	0.449	0.654	-0.005	0.008
weight	-6.439e-05	0.012	-0.005	0.996	-0.024	0.024
percent_reciprocal	0.2783	0.307	0.906	0.365	-0.324	0.881
likes_std	-0.0356	0.065	-0.551	0.582	-0.162	0.091
act_pre_peak	-0.0035	0.003	-1.165	0.244	-0.009	0.002

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 1. Dependent variable here is the interval, in minutes, from the time of the peak of activity to the first tweet of a user in a different protest network. The selected model for period 1 and interval as dependent variable was the same for both forward and backward step-wise searches.
* $p < .05$

Table A.6

Generalized Linear Regression for Period 2: Interval, Step-wise Search

Dep. Variable:	interval_minutes	**No. Observations:**	813
Model:	GLM	**Df Residuals:**	805
Model Family:	NegativeBinomial	**Df Model:**	7
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-8112.5
Date:	Sun, 20 Feb 2022	**Deviance:**	814.22
Time:	13:58:13	**Pearson chi2:**	635.
No. Iterations:	9	**Pseudo R-squ. (CS):**	0.01028
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	4.5759	0.051	90.262	0.000*	4.477	4.675
lang_diff[T.True]	4.5759	0.051	90.262	0.000*	4.477	4.675
age[T.30-39]	-0.2628	0.155	-1.693	0.090	-0.567	0.041
age[T.<=18]	-0.0930	0.145	-0.640	0.522	-0.378	0.192
age[T.>=40]	-0.1933	0.123	-1.567	0.117	-0.435	0.048
gender[T.True]	0.1045	0.102	1.021	0.307	-0.096	0.305
int_pre_peak	5.925e-05	0.015	0.004	0.997	-0.029	0.029
likes_std	-0.3982	0.374	-1.065	0.287	-1.131	0.335
act_pre_peak	-0.0029	0.014	-0.208	0.835	-0.030	0.024

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 2. Dependent variable here is the interval, in minutes, from the time of the peak of activity to the first tweet of a user in a different protest network. The selected model for period 2 and interval as dependent variable was the same for both forward and backward step-wise searches.
$^{*}p < .05$

Table A.7

Generalized Linear Regression for Period 3: Interval, Step-wise Search

Dep. Variable:	interval_minutes	**No. Observations:**	744
Model:	GLM	**Df Residuals:**	739
Model Family:	NegativeBinomial	**Df Model:**	4
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-6846.4
Date:	Sun, 20 Feb 2022	**Deviance:**	802.78
Time:	15:05:22	**Pearson chi2:**	791.
No. Iterations:	10	**Pseudo R-squ. (CS):**	0.009193
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	4.2088	0.041	103.599	0.000*	4.129	4.288
lang_diff[T.True]	4.2088	0.041	103.599	0.000*	4.129	4.288
gender[T.True]	-0.0146	0.107	-0.136	0.891	-0.224	0.195
int_pre_peak	-0.0211	0.035	-0.603	0.547	-0.090	0.047
norm_act_pre_peak_avg	-0.0005	0.002	-0.301	0.764	-0.004	0.003
act_pre_peak	-0.0105	0.032	-0.329	0.742	-0.073	0.052

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 3. Dependent variable here is the interval, in minutes, from the time of the peak of activity to the first tweet of a user in a different protest network. The selected model for period 3 and interval as dependent variable was the same for both forward and backward step-wise searches.
$^{*}p < .05$

Table A.8

Generalized Linear Regression for Period 1: Cluster Change, Forward Step-wise Search

Dep. Variable:	same_cluster_change	**No. Observations:**	1904
Model:	GLM	**Df Residuals:**	1899
Model Family:	Gaussian	**Df Model:**	4
Link Function:	identity	**Scale:**	0.17505
Method:	IRLS	**Log-Likelihood:**	-1040.1
Date:	Sun, 20 Feb 2022	**Deviance:**	332.42
Time:	13:55:54	**Pearson chi2:**	332.
No. Iterations:	3	**Pseudo R-squ. (CS):**	0.001916
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	-0.2228	0.022	-10.355	0.000*	-0.265	-0.181
age[T.30-39]	-0.0102	0.030	-0.342	0.733	-0.068	0.048
age[T.<=18]	0.0232	0.042	0.552	0.581	-0.059	0.105
age[T.>=40]	-0.0339	0.025	-1.346	0.178	-0.083	0.015
org[T.True]	0.0136	0.027	0.509	0.611	-0.039	0.066

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 1. Dependent variable here is the interval, in minutes, from the time of the peak of activity to the first tweet of a user in a different protest network. The model was selected here with a forward step-wise search.
$^{*}p < .05$

Table A.9

Generalized Linear Regression for Period 1: Cluster Change, Backward Step-wise Search

Dep. Variable:	same_cluster_change	**No. Observations:**	1904
Model:	GLM	**Df Residuals:**	1894
Model Family:	Gaussian	**Df Model:**	9
Link Function:	identity	**Scale:**	0.17424
Method:	IRLS	**Log-Likelihood:**	-1033.2
Date:	Sun, 20 Feb 2022	**Deviance:**	330.02
Time:	13:55:54	**Pearson chi2:**	330.
No. Iterations:	3	**Pseudo R-squ. (CS):**	0.009152
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	-0.2502	0.024	-10.592	0.000*	-0.297	-0.204
org[T.True]	0.0141	0.027	0.528	0.598	-0.038	0.067
age[T.30-39]	-0.0114	0.030	-0.383	0.702	-0.070	0.047
age[T.<=18]	0.0181	0.042	0.432	0.665	-0.064	0.100
age[T.>=40]	-0.0342	0.025	-1.360	0.174	-0.084	0.015
act_post_peak_avg	0.0031	0.011	0.280	0.779	-0.018	0.024
norm_act_pre_peak_avg	0.0005	0.000	1.375	0.169	-0.000	0.001
weight	9.6e-05	0.000	0.445	0.656	-0.000	0.001
likes_std	0.0083	0.007	1.275	0.202	-0.004	0.021
act_pre_peak	0.0001	7.57e-05	1.357	0.175	-4.56e-05	0.000

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 1. Dependent variable here is the interval, in minutes, from the time of the peak of activity to the first tweet of a user in a different protest network. The model was selected here with a backward step-wise search.
$^{*}p < .05$

Table A.10

Generalized Linear Regression for Period 2: Cluster Change, Forward Step-wise Search

Dep. Variable:	same_cluster_change	**No. Observations:**	1496
Model:	GLM	**Df Residuals:**	1488
Model Family:	Gaussian	**Df Model:**	7
Link Function:	identity	**Scale:**	0.31201
Method:	IRLS	**Log-Likelihood:**	-1247.5
Date:	Sun, 20 Feb 2022	**Deviance:**	464.27
Time:	13:57:49	**Pearson chi2:**	464.
No. Iterations:	3	**Pseudo R-squ. (CS):**	0.003137
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	-0.3099	0.035	-8.830	0.000*	-0.379	-0.241
age[T.30-39]	0.0220	0.045	0.486	0.627	-0.067	0.111
age[T.<=18]	0.0590	0.048	1.220	0.223	-0.036	0.154
age[T.>=40]	0.0331	0.036	0.907	0.365	-0.038	0.105
gender[T.True]	-0.0291	0.029	-0.988	0.323	-0.087	0.029
org[T.True]	0.0423	0.040	1.053	0.292	-0.036	0.121
norm_act_pre_peak_avg	-7.072e-06	0.001	-0.013	0.990	-0.001	0.001
act_pre_peak	-0.0006	0.001	-0.604	0.546	-0.003	0.001

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 2. Dependent variable here is the interval, in minutes, from the time of the peak of activity to the first tweet of a user in a different protest network. The model was selected here with a forward step-wise search.
$^{*}p < .05$

Table A.11

Generalized Linear Regression for Period 2: Cluster Change, Backward Step-wise Search

Dep. Variable:	same_cluster_change	**No. Observations:**	1496
Model:	GLM	**Df Residuals:**	1486
Model Family:	Gaussian	**Df Model:**	9
Link Function:	identity	**Scale:**	0.31198
Method:	IRLS	**Log-Likelihood:**	-1246.4
Date:	Sun, 20 Feb 2022	**Deviance:**	463.61
Time:	13:57:49	**Pearson chi2:**	464.
No. Iterations:	3	**Pseudo R-squ. (CS):**	0.004563
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	-0.3131	0.035	-8.909	0.000*	-0.382	-0.244
org[T.True]	0.0379	0.040	0.940	0.347	-0.041	0.117
age[T.30-39]	0.0191	0.045	0.420	0.674	-0.070	0.108
age[T.<=18]	0.0597	0.048	1.233	0.217	-0.035	0.154
age[T.>=40]	0.0312	0.037	0.854	0.393	-0.040	0.103
gender[T.True]	-0.0299	0.029	-1.016	0.310	-0.088	0.028
act_post_peak_avg	0.0235	0.045	0.525	0.599	-0.064	0.111
norm_act_pre_peak_avg	-0.0001	0.001	-0.209	0.835	-0.001	0.001
weight	-0.0004	0.001	-0.438	0.661	-0.002	0.001
likes_std	0.0870	0.066	1.311	0.190	-0.043	0.217

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 2. Dependent variable here is the interval, in minutes, from the time of the peak of activity to the first tweet of a user in a different protest network. The model was selected here with a backward step-wise search.
$^{*}p < .05$

Table A.12

Generalized Linear Regression for Period 3: Cluster Change, Forward Step-wise Search

Dep. Variable:	same_cluster_change	**No. Observations:**	888
Model:	GLM	**Df Residuals:**	879
Model Family:	Gaussian	**Df Model:**	8
Link Function:	identity	**Scale:**	0.20538
Method:	IRLS	**Log-Likelihood:**	-552.68
Date:	Sun, 20 Feb 2022	**Deviance:**	180.53
Time:	15:05:07	**Pearson chi2:**	181.
No. Iterations:	3	**Pseudo R-squ. (CS):**	0.005771
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	-0.1874	0.028	-6.639	0.000*	-0.243	-0.132
age[T.30-39]	-0.0412	0.042	-0.973	0.331	-0.124	0.042
age[T.<=18]	0.0207	0.046	0.454	0.650	-0.069	0.110
age[T.>=40]	-0.0216	0.040	-0.545	0.586	-0.100	0.056
org[T.True]	0.0601	0.054	1.112	0.266	-0.046	0.166
reciprocal	4.145e-05	0.003	0.013	0.989	-0.006	0.006
int_pre_peak	-0.0006	0.003	-0.174	0.862	-0.007	0.006
act_pre_peak	0.0009	0.003	0.370	0.711	-0.004	0.006
likes_std	0.0511	0.052	0.992	0.321	-0.050	0.152

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 3. Dependent variable here is the interval, in minutes, from the time of the peak of activity to the first tweet of a user in a different protest network. The model was selected here with a forward step-wise search.
$^{*}p < .05$

Table A.13

Generalized Linear Regression for Period 3: Cluster Change, Backward Step-wise Search

Dep. Variable:	same_cluster_change	**No. Observations:**	888
Model:	GLM	**Df Residuals:**	875
Model Family:	Gaussian	**Df Model:**	12
Link Function:	identity	**Scale:**	0.20423
Method:	IRLS	**Log-Likelihood:**	-548.17
Date:	Sun, 20 Feb 2022	**Deviance:**	178.70
Time:	15:05:07	**Pearson chi2:**	179.
No. Iterations:	3	**Pseudo R-squ. (CS):**	0.01581
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	-0.2010	0.041	-4.882	0.000*	-0.282	-0.120
lang_diff[T.True]	0.0454	0.033	1.362	0.173	-0.020	0.111
org[T.True]	0.0456	0.054	0.840	0.401	-0.061	0.152
age[T.30-39]	-0.0264	0.043	-0.610	0.542	-0.111	0.059
age[T.<=18]	0.0213	0.046	0.467	0.641	-0.068	0.111
age[T.>=40]	-0.0096	0.043	-0.226	0.821	-0.093	0.074
gender[T.True]	-0.0411	0.032	-1.303	0.193	-0.103	0.021
act_post_peak_avg	0.0005	0.035	0.015	0.988	-0.067	0.068
act_pre_peak_avg	0.1100	0.099	1.116	0.264	-0.083	0.303
int_pre_peak	-0.0001	0.003	-0.045	0.964	-0.007	0.006
weight	0.0023	0.002	1.062	0.288	-0.002	0.007
likes_std	0.0522	0.052	1.009	0.313	-0.049	0.153
act_pre_peak	-0.0047	0.004	-1.119	0.263	-0.013	0.004

Note. This table shows an example statistical output for the time-aggregated approach in Article I in sampled period 3. Dependent variable here is the interval, in minutes, from the time of the peak of activity to the first tweet of a user in a different protest network. The model was selected here with a backward step-wise search.
$^{*}p < .05$

Appendix B

Article II

B.1 Data Augmentation

The following prompt was the prompt provided to GPT-4 for data augmentation of each example coded in each category.

> **System prompt:** You are an advanced AI writer. Your job is to help write examples of sentences or paragraphs that appear in news articles about accusations of sexual harassment, sexual violence, or rape. You will be provided with human annotated examples of this social dimension.
>
> **Prompt:** These example statements are ones where <*code description*>.
>
> **Example:**
>
> - <*example provided*>
>
> **Task:** Using the human annotated example above and incorporating the social dimension from the Prompt, generate 10 new semantically similar statements that do not contain explicit language in the style of the examples with the social dimension. Do in the same language.

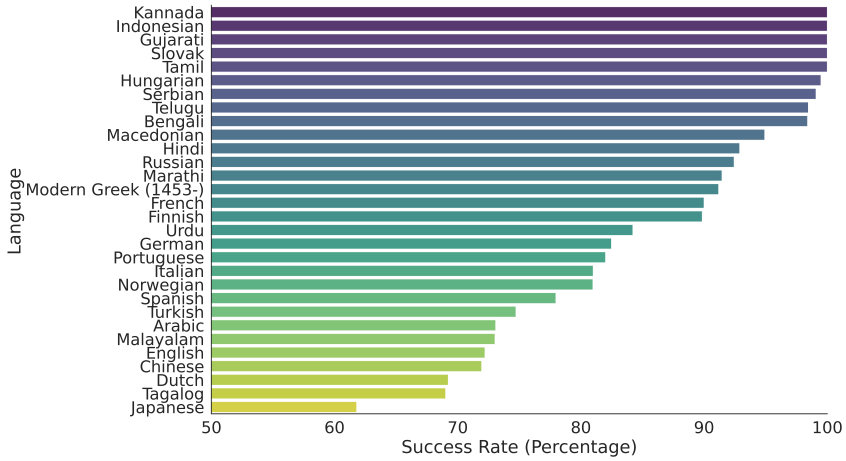
Some prompts returned no responses from GPT-4 as it stated that the returned results would violate their terms of service. No augmentation was carried out with these examples.

B.2 Media Enrichment

Figure B.1 shows the success rate of enrichment of media by language.

Figure B.1

Enrichment Success Rate



Note. This figure shows the enrichment success rate by language for the collected news articles. Kannada, Indonesian, Gujarati, Slovak, and Tamil all have 100% success rate due to a very low (<10) number of total articles.

B.3 Media Cloud Query

Variations and translations of #MeToo were employed in the search query in Media Cloud, on top of the collecting articles that contained various combinations of 'allegations', 'accuse', 'claim' and 'sexual assault', 'sexual harassment', 'rape'. These are displayed in Figure B.2. Please note that Article III points here because it used the same distribution of languages.

B.4 Thresholds for Relevance and Substantive Rape Myth Classification

Figure B.3 shows the distribution of the substantive labeling and their logit cumulative distributions. Only logits above 0.99 were considered the analysis.

B.5 Detected Peaks of Media Coverage about #MeToo

Figure B.4 shows the peaks taken for each country in for the BSTS intervention analysis. Peaks were detected after 2017 and from articles that mention #MeToo or one of its known versions explicitly.

Figure B.2

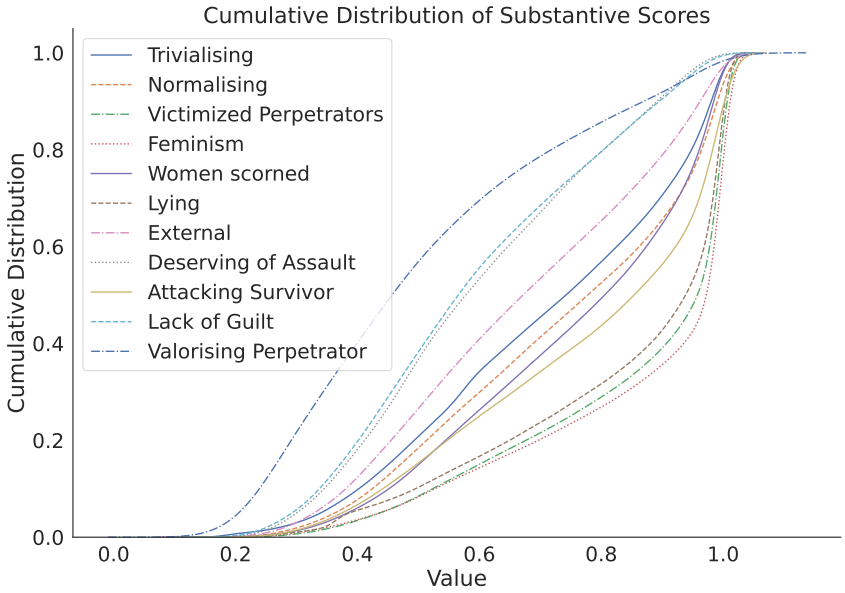
Hashtags Used in Media Cloud Query

metoo	niunamenos
timesup	kutoo
cuentalo	withyou
balancetonporc	noustoutes
wetoo	나도
moiaussi	yotambien
quellavoltache	sendeanlat
ricebunny	私も
enazeda	我也是
woyeshi	memyös
jotambe	米兔
niere	stilleforopptak
نه_یعنی_نه	myharveyweinstein
gamani	ятоже
anakaman	nårmusikkenstilner
ונחנאסג	tôicũngvậy
watashimo	nårdansenstopper
나도당했다	نامك انأو

Note. This figure shows the hashtags used in the query to Media Cloud, in addition to searching for articles about sexual assault, harassment, and public allegations thereof.

Figure B.3

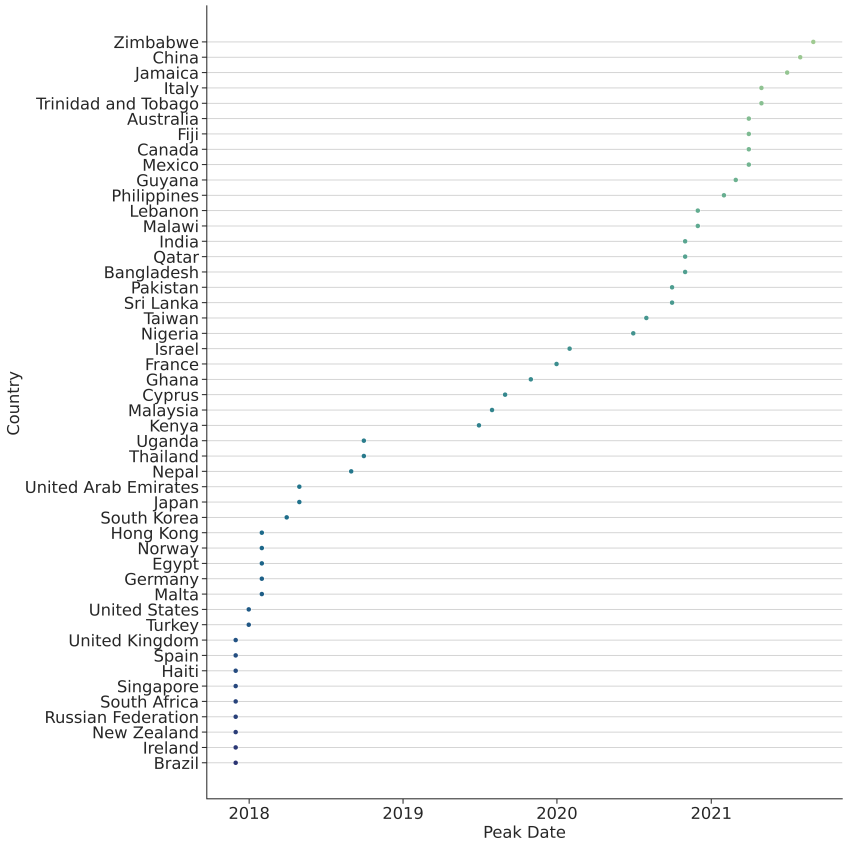
Distribution of 'Rape Myth' Labels and their Logits.



Note. This figure shows distributions of logits for the rape myths. To reduce false positive rate, only sentences with logits above 0.99 in any given rape myth category were considered for subsequent analysis.

Figure B.4

Peaks of Coverage



Note. This figure shows the detected peaks of overage for each country. These detected peaks were then subsequently used for the intervention analysis.

Appendix C

Subject: Collaboration with Hubert Au

April 19, 2024

Dear Oxford Graduate Studies Committee/Examiners,

This letter is to certify that Hubert Au was the primary author of our article "The Effect of #MeToo on Rape Myths in the Media: A Global Multilingual Analysis". Hubert conceived of the piece, gathered and cleaned the data, conducted a literature review, and drafted the manuscript. I helped qualitatively annotate the rape myths identified by Hubert in the literature review to enable the subsequent steps of the analysis, which Hubert carried out without my help.

In summary, the work is almost entirely his own, and I have no objections to him submitting a lightly revised version of the article as a chapter of his doctoral thesis. Please do not hesitate to reach out if you have any questions.

Sincerely,



Joana Perrone

Doctoral Candidate

Oxford School of Global and Area Studies

Telephone: +44 7474 079930

Email: joana.perrone@wadham.ox.ac.uk