The role of connectivity in social change

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1 Introduction

Social movements are a significant force in societal change [1]; notable examples of impactful social movements include the civil rights movement of the 1960s [2] and the Arab spring of the early 2010s [3], both producing tangible changes in lifestyle for affected individuals in a society. Studies of collective behaviour, in the context of social movements, have produced various frameworks for understanding revolutions and how they develop. This has allowed for the application of modelling techniques, such as agent-based models (ABMs) [4], to attempt to capture the dynamics of social movements and produce insights into the likelihood of a revolution being successful. The literature discusses the importance of several underlying concepts that contribute to the emergence of social revolutions, including preference falsification, diverse individual thresholds, social structures, and authoritarian resistance and control. Using these concepts as a foundation, we develop and ABM approach to investigate the impact that social media has on social revolutions.

1.1 Preference Falsification

Preference falsification, first described in [5], is the idea of communicating a public belief that differs from an internal, private belief. This is often widespread in "oppressive regimes", due to the fear of punishment or ostracization [6]. Sunstein in [6] highlights that this is an important part of social revolutions, using the #MeToo movement as a motivating example. The idea is that individuals often do not know what other people in their networks truly believe. Therefore, even though their opinion may be mainstream, they think that is will be perceived negatively by their network, discouraging them from making their true belief public [6]. In the case of the #MeToo movement, individuals were scared to publicly confront their sexual abusers since they thought that society would not believe they stories [6]. However, when enough people in their network come forward publicly, it encourages them to also reveal their true beliefs due to the social support [6]. As a result, there tends to be seemingly sudden bursts of public opinion shift, where individuals feel comfortable to share their true beliefs. This phenomenon can be a critical driver in rapid social movements.

1.2 Thresholds

Another idea discussed in [6] and originally investigated in [7], is the diversity of belief thresholds among people in a population. Belief thresholds is the concept that different people require different levels of social support before joining a movement [6]. For instance, some people may be particularly haphazard and actively display their true beliefs against a central authority despite having no social support. They do so despite knowing that they may be punished or reprimanded for such public dissent. In contrast, other people may be particularly conservative and never display their true dissenting beliefs. [7] proposes that people lie somewhere on this spectrum of thresholds. They propose a number of models of collective behaviour related to different threshold distributions and discusses the implications of each on the development and final size of a movement. A limitation outlined in [7] about the investigation is the limited utility of the modelling without "empirical or theoretical reason to expect one particular distribution over another"; this is supported in [6] which describes the impossible nature of assessing a population's true threshold distribution. Without experience rebelling against authority, it is difficult to know ones own threshold, much less the thresholds of everyone in society. This proposes a modelling challenge, since it is both essential to the underlying nature of social revolutions and difficult to model accurately. However, [7] offer a range of distributions which reflect observations in the real world, providing a useful platform to develop a model.

1.3 Social Structures

The social structure of societies is another critical concept which has "important but complex relationships" [7] to the dynamics of a social movement. Interdependence between individuals in a population have a direct impact on the development of a revolution, specifically affecting each person's assessment of the strength of a movement; the importance of the initial phase of a rebellion being witnessed is discussed in [6]. For example, consider a social structure whereby people are isolated and disconnected. Here, the lack of connection between individuals makes revolutions difficult to spread. Now, consider a case where there are strong connections between individuals in society. Here, when an individual starts to display a belief against an authority, they are more likely to be supported by other members of society, creating a knock-on effect which leads to a social revolution. Social media has significantly changed the structure of social networks. These effects are discussed in section 1.5.

1.4 Punishment and control

Often, social revolutions occur against a central authority or system that attempts to suppress the revolution [8]. In the case of the Arab Spring and civil rights movements, the central authority is the controlling government [3], whereas with the #MeToo movement, the central authority is the patriarchal system that allows sexual abuse to occur [6]. The central authority often uses tactics such as punishment, suppression and ostracism to prevent the disturbance of power [4], [6]. Previously, ABM approaches have modelled punishment and control with decentralised agents who enforce authority by punishing those with dissident beliefs and/or behaviours [8]. However, in their review of social media and social movements, Kidd and McIntosh [9] highlight that the way authoritarian forces monitor and control dissident behaviour has changed with modern technology. They suggest that the internet is a powerful tool used by authoritarian governments to track, infiltrate and undermine counter political movements in a more organised and centralised way [9]. A good example of modern technology-based authoritarianism is China, who use the internet for "ubiquitous mass surveillance" [10], leading to the real-time ability to enforce laws and regulations, thereby maintaining social norms [10]. This suggests that modelling punishment and control through a centralised authority system rather than decentralised agents may be more appropriate.

1.5 Social Media

The rise of the internet and social media presents a significant change to traditional social networks, reducing the barrier to connection and communication for individuals in a population. Research done around general internet usage has found that higher internet usage rates correlates with a tendency for weaker social ties to exist in an individual's network [11]. Although connection between individuals is more accessible, those connections become more superficial, deteriorating the strength of connections. The influence of social media on social networks is further explored in [12], which argues that the typical size of each network has grown with the introduction of online communication. This point is extended by Turkle in [13], who supports the notion that the nature of the relationships in these extended networks are often more superficial.

The effect of social media on social revolutions has been examined in various studies. Sunstein [6] notes in their discussion of the #MeToo movement that social media provided increased awareness and a platform for people to speak up. This suggests that social media in some cases has helped create a more open, interconnected society. Work done in [14] describes the role social media played, namely Twitter, in the development of the 2011 Tunisian and Egyptian Revolutions; Lotan, Graeff, Ananny, *et al.* tracks the flow of information and roles of different social media users in the spread of civil unrest. They note that social media contributes to the spread and effectiveness of social revolutions through increased local and global awareness, organisation of information and communication, and the documentation of the true actions and beliefs of participating individuals [14].

1.6 Literature Gap and Question

Applications of agent-based modelling in the study of social movements have captured various aspects of social movement dynamics. Lemos, Coelho, and Lopes [4] provides an overview of a broader set of social conflict ABMs, comparing the qualitative and quantitative analysis produced by each. A widely discussed model of civil violence produced from [8] simulates the interactions between people and a police force (decentralised authority) in a rebellion. While the model provides a foundational ABM approach to modelling social revolutions, [4] notes that the implementation of the movement of agents is unrealistic. Moreover, as previously discussed, authority has become more centralised with technological advances. This suggests that a more effective way to model social revolutions may be to model the society as a network where edges represent connections between agents rather than explicitly modelling agents spatially, with punishments done by a central figure.

Another ABM for social revolutions, proposed in [15], examines social movements and the role of connectivity in its success. Central and non-central authorities and citizens are modelled, with each agent working to maximise some utility function relating to their own goals and risks. Although they investigate the impacts of increased communication resulting from social media, they do not investigate how the structural changes to social networks, resulting from social media, has impacted on social revolutions.

This leaves a gap in the research, to investigate how social media's impact on the structure of social networks and authoritarian control has effected social revolutions.

2 Question

How does the change to the structure of social networks, as a result of social media, influence the public beliefs of individuals in society, and how can this lead to social revolutions?

3 Model Design (ODD)

3.1 Purpose

The purpose of the model is to assess the influence social media and technology have on the connectivity and structure of social networks, how these changes impact the public beliefs of individuals, and whether this can have a knock-on effect which ultimately leads to a social revolution.

3.2 Entities, state variables and scales

Global Variables:

1. **Number of people:** The size of the population.
2. **Mean edge strength:** The average strength of connection between two connected agents.
3. **Number of connections:** The number of people in an agents network.
4. **Punishment chance:** The probability that an agent is punished if they display an "against" belief.
5. **Punishment Level:** The severity of the punishment. This is a number between 0 and 1, where 1 is the most severe punishment.
6. **Rewiring probability:** This is the probability that an initial connection between an agents and a neighbouring agent gets rewired to become a connection

with some other agent. A higher rewiring probability represents the effect of social media, whereby the world is more globally interconnected rather than relationships being entirely localised.

There is only one type of agent in the model. These are agents which represent people in a society. They are categorised by the following state variables:

1. **Private belief:** The true belief of an individual. This is binary, with agents being either "for" or "against" some authority.
2. **Public belief:** The belief that the individual displays publicly. This is also either "for" or "against".
3. **Threshold:** A threshold value that, when reached, will cause the individual to make their private belief public. See sub-models for more details.
4. **Network connections:** A group of other agents that are within the agents network, and the strength of the pairwise connection. The strength is taken from an exponential distribution with a mean set by the global variable *mean edge strength.*

The scales in the model are as follows:

1. **Time:** The time-steps represent days. This gives enough time for agents to view other agents public beliefs and change their public beliefs accordingly.
2. **Space:** Space is not represented in the model. Networks are treated as a more abstract concept where space is not important.

3.3 Process overview and scheduling

See sub-models for more details on each process.

1. The environment is **set-up**
2. While public beliefs are still changing:
    (a) Individuals **view** the public beliefs of their network.
    (b) Individuals **update** their own public beliefs.
    (c) Individuals who change their public belief from "for" to "against" may get **punished**.

3.4 Design concepts

The **basic principles** in the model are preference falsification, thresholds, punishment and control and social media. The literature review provides a discussion of these principles and how the contribute to the emergence of social revolutions in theory. Preference falsification is modelled through the agent variables public belief and private belief, which may differ from each other. Each agent's threshold for changing their public opinion to match their private opinion follows the threshold model [7]. Some agents are 'zeroes': they do not require any other agents in their network to have the same public opinion in order to voice their own. Others require one agent to have the same public opinion before they will join in, and so on. Punishment and control is represented by a centralised authority who probabilistically punishes agents they change their public belief to "against". The impact of a punishment is to deter other agents from showing dissident beliefs. Social media is represented in the model by different network structures, including different edge strength distributions, number of connections and rewiring probability.

Emergence occurs through revolutions. A revolution is when lots of agents change their public belief from "for" to "against". Whether a revolution emerges changes in complex ways depending on variations in different parameters. The purpose of this study is to investigate of different parameters may impact the emergence of revolutions.

The public belief of an individual is a demonstration of **Adaptation**, as each agent decides their public opinion based on the other agents in their network. Thresholds also adapt through punishments. When an agent gets punished, the agents in the network become deterred and therefore increase their thresholds.

Agents are able to **sense** the public opinion of other agents in their network, as well as their own private and public opinion. In addition, while they are not 'consciously aware' of their own threshold level, it is used by the agent when making decisions. Agents are also able to sense when someone in their network has been punished.

Each agent **interacts** with the other agents in their network, as their own public opinion can affect the public opinion of those connected to them. Moreover, the punishment of an agent affects the thresholds of connected agents, constituting a form of punishment.

There is **stochasticity** in the network connections and their strengths, as well as in the agent's threshold levels which are drawn from a distribution. Additionally, agents are punished with some probability if they change their public belief to "against".

Agents are able to **observe** the public beliefs of connected agents at each time step. Moreover, when an agent is punished, connected agents observe this punishment.

3.5 Initialisation

The initialisation of parameters were collectively chosen to allow for variable results in experiments. The default values of the parameters reflect a situation where there are neither never revolutions nor always revolutions. This is a Pattern-Oriented Modelling approach where the default model reflects what we qualitatively observe.

1. **Number of people:** This was set to 100 people
2. **Mean edge strength:** Varied in the experiments. If it was not a varied parameter it was set to 0.5. 0 represents no connection while 1 represents a complete, strong connection.
3. **Number of connections:** Varied in experiments. If it was not varied, it was set to 80.
4. **Punishment Chance:** Varied in experiments. If it was not varied, it was set to 0.5.
5. **Punishment Level:** Varied in experiments. If it was not varied, it was set to 0.5.
6. **Rewiring probability:** Varied in experiments. Set to 0.3 by default.
7. **Private belief:** "Against" for all agents.

8. **Public belief:** "For" for all agents.

9. **Threshold:** Drawn from a gamma distribution $\alpha = 2.5$ and a $\beta = 0.4$. This captures the variability of threshold values in society [7]. The values for α and β were chosen in combination with the default parameters as described above. In the case where there are no agents with a threshold of zero, a random agent is reassigned a threshold of zero to ensure at least one agent will revolt.

10. **Network connections:** Networks of size *number of connections* were created with the strength of those connection drawn from an exponential distribution with mean *mean edge strength*. If an edge strength was greater than 1 or less than 0, it was redrawn. The idea of using an exponential distribution is to represent real-life relationships, where people tend to have few very strong connections and many weak connections.

3.6 Input

The environment is assumed to be constant, so the model has no input data.

3.7 Sub-models

1. **Set-up:** Individuals are assigned their threshold, private belief, public belief, position and networks as defined in the initialisation.

2. **View beliefs:** At each time-step, individuals view and record the public beliefs of all the other individuals in their network.

3. **Update beliefs:** As each time-step, all individuals update their current public beliefs according to the following rule:

    - Take W as the weighted sum of all the people in the agents network that have the same *public belief* as the agents *private belief*, where the weights are the strength of the connection.
    - If $W >$ *threshold* then make public belief private belief.
    - Otherwise keep public belief as before.
    - If public belief changes from "for" to "against" then complete a once off **punishment**.

4. **Punishment:** Punishment of individuals follows the procedure:

    - Pick a random number between 0 and 1.
    - If the number is less than the *punishment-chance*, then for all agents in the punished agents network, increase their threshold by the *punishment-level* $*$*edge-strength*.

    The idea is that punishment deters other agents who are connected to the punished agent from becoming dissident. This occurs through an increase in their threshold. In other words, they become less likely to join the revolution.

4 Methods

Each experiment measures the effect of varying specific parameters on the total size of a revolution (i.e. the number of individuals who alter their public belief to reflect their private belief). This was deemed an indicative measure as it reflects the extent to which a particular parameter setting produced a mass movement. Experiments were repeated 40 times to ensure an accurate assessment of each setting was ascertained. A set of parameter values were found that produced a general revolution size that allowed for variable results in each experiment. These were also chosen using a Pattern-Oriented Modelling approach to capture a number of the qualitative characteristics of revolutions and social media found in the literature.

4.1 Edge Strength and Number of Connections

The effect of connection strength between individuals in a population was measured by altering the mean of the distribution each edge strength was sampled from. This allows for testing in a number of settings related to different general levels of connectivity strength in a community. *Mean edge strength* was varied between 0-1.0 in increments of 0.025.

The number of connections each individual had within the population was also tested. *Number of connections* was varied between 2-100 in increments of 4.

In addition to the above two experiments, a further investigation of the interplay between the two variables was carried out; this involved varying both parameters over the same ranges with slightly coarser increments (0.1 for *Mean edge strength* and 8 for *Number of connections*), due to limited resources in the testing environment. This experiment was done to investigate the relationship between the two variables and confirm a number of general trends around the effect of connectivity on revolution size.

4.2 Punishment and Control

As discussed in section 1.4, social media has changed the nature and effectiveness of how central authorities utilise punishment and control. Therefore, it is important to vary these effects to fully ascertain the impact of social media on social revolutions. We considered the effect of two variables that impact punishment in different ways.

1. The **probability of punishment**. The idea is that social media provides better surveillance for central authorities, enhancing the probability that the central authority will detect and thereafter punish dissident civilians [9]. To measure the impact of the probability of punishment, we varied the *punishment-chance* between 0 and 1 in increments of 0.04, recording the number of people who are publicly "against" the central authority at the end of the simulation for each probability.

2. The **severity of punishment**. This is important to investigate since different authorities assert their control at varying levels. We investigated the effect

of punishment severity on social revolutions by varying the *punishment-level* between 0 and 1 in increments of 0.04, recording the number of people who are publicly "against" the central authority at the end of the simulation for each *punishment-level*.

We also note that the level and probability of punishment are inherently related. Therefore, it is important to consider the joint effect of *punishment-level* and *punishment-probability* on the revolution size. This was done by varying both parameters between 0 and 1 in increments of 0.1, leading to a total of 100 parameter combinations.

4.3 Network Structure (Rewiring probability)

The structure of the network was varied to measure its effect on the revolution of the agents. Initially, each agent is connected to its nearest 30 neighbours. This results in a network with a high clustering coefficient as each agent is wired to their local neighbours. From this starting point, each wired connection is rewired with probability determined by the *rewiring probability*. The total number of connections remains fixed, but as the rewiring probability increases, the connections become less localised.

The total number of agents publicly 'against' was measured over a rewiring probability from 0 to 1.0, in 0.1 increments.

In order to isolate the effect of network structure, *punishment chance* was set to zero, and *mean edge strength* set to one.

5 Results & Discussion

5.1 Bimodal Nature of Social Revolutions

Figure 1 demonstrates the bimodal nature of revolutions. The two peaks at 0% and 100% of the population who are publicly "against" the central authority indicates that either a revolution gets 'squashed' early and dies out, or the entire population joins. The first case would be an unsuccessful revolution and the second case would be a successful revolution. In the context of preference falsification and thresholds, discussed in the introduction, when revolutions gain traction early, the increased number of individuals with publicly "against" beliefs has a knock-on effect, whereby other agents view this public display of dissent, and join in since there are enough individuals against the government to surpass their threshold. In other words, agents recognise the social support for their private beliefs, and therefore they feel comfortable in making their true, private belief public. This propagates throughout the network, leading to complete revolutions. In contrast, if the revolution does not gain early traction, it quickly dies out since there are not enough dissenting agents to surpass the thresholds of sufficiently many other agents.

Figure 2 demonstrates the gamma distribution of thresholds, with the chosen parameters, used in the modelling process. Evidently, there is a concentration of agents with thresholds between 4 and 5. For agents to publicly display their "against" beliefs, the weighted average number of connected agents with public "against" beliefs needs to surpass their threshold, where the weights are the strength of the connection. The concentration of agents with similar thresholds leads to some critical number of individuals that need to join in the revolution for it to be effective. Thereafter, the revolution is very difficult to halt. This makes sense, both in the context of the research in [7] and the the nature of revolutions in real life, whereby social revolutions tend to happen in rapid and complete shifts in public opinion.

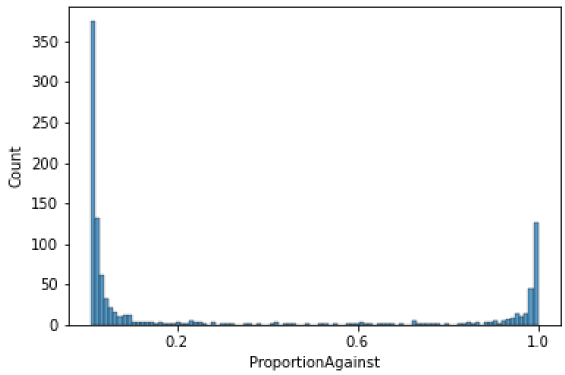


Figure 1: Histogram of the proportion of the population with beliefs "against" the central authority for each run. All results across the experiments discussed above were included in the histogram.

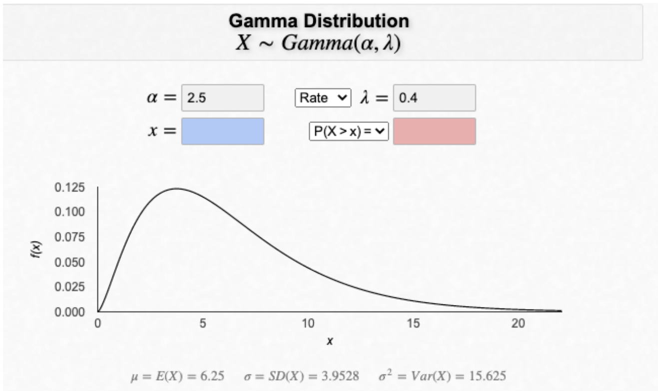


Figure 2: Distribution of the thresholds. Gamma distribution generated at: `https://homepage.divms.uiowa.edu/~mbognar/applets/gamma.html`

5.2 Edge Strength and Number of Connections

The results of the experiments relating to edge strength and number of connections are shown in figures 3, 4 and 5.

The results from experimentation relating to varying number of connections confirm an expected trend and provide a useful insight into the effect of social media on social movements. The general trend present in figure 4 that mean revolution size increases as number of connections increase, was largely an expected relationship. This makes intuitive sense as the more connected an individual is within a society, the more likely that individual

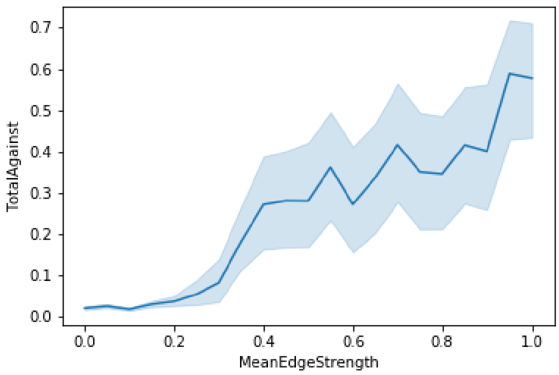


Figure 3: Effect of variable mean edge strength on the mean revolution size. The light blue region surrounding the line represents a 95% confidence interval.

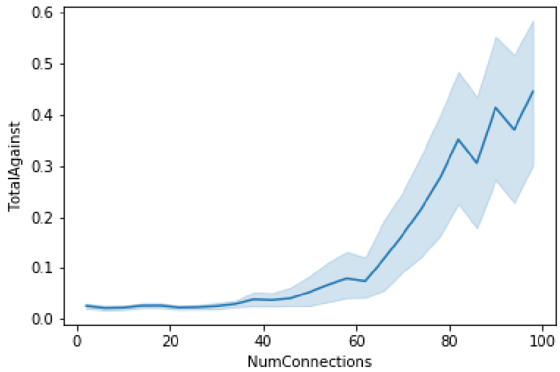


Figure 4: Effect of individual's number of connections on the mean revolution size. The light blue region surrounding the line represents a 95% confidence interval.

is to be connected to people who are joining the social movement. The higher variability of the results as number of connections increases beyond 60 is likely indicative of the polarised, bimodal results as discussed above. Relating this trend to the idea proposed in [12], that social media generally increases an individual's social network size, this positive relationship suggests social media has a positive effect of revolution development. This corresponds with other research in [6] and [14] which suggests social media has a positive effect on social movement development.

Alternatively, examining results shown in figure 3, relating to the effect of edge connections on social movement size, may indicate the relationship social media has with revolution size is less clear. The general trend indicates increasing the mean edge strength amongst individuals in a population, increases the mean revolution size; this is largely expected as connection strength plays a key role in determining if a person changes their public belief. Similarly to the trend explored in relation to varying number of connections, the increased variability of the results as mean edge strength increases towards 1.0 is reflective of the bimodal results. The rate of increase is notably appearing to climb gradually between $0.3 - 1.0$; this may be indicative that the parameter of mean edge strength is less sensitive compared to other factors such as number of connections.

Examining this result in the context of the influence of social media, it may indicate the effect of social media on revolution size is more complex. The theory described in [13], that social media is encouraging more superficial, weaker relationships, and the finding in these results that generally weaker connections have a detrimental effect on social movement size, may suggest that in this respect, social media has a negative effect on revolution development. It should be noted this trend only describes part of the overall picture, similar to the effect of network size, and the influence of each of these consequences of social media is debatable.

The heat-map shown in figure 5 describes the relationship between the number of connections, mean edge relationship and revolution size. These results largely agree with the general trends described in the previous discussion with the higher mean revolution size generally being

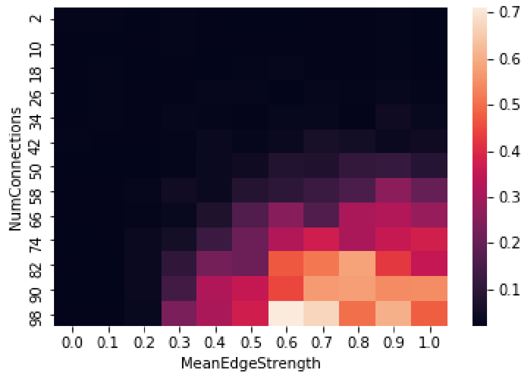


Figure 5: Effect of individual's number of connections and mean edge strength on the mean revolution size.

produced in the higher mean edge strength and higher number of connections section of the map (bottom right corner). Both parameters have some range (2-42 connections for number of connections and 0-0.2 for mean edge strength) where revolutions are largely not possible; this correlates with the previous discussion that both parameters play a significant role in revolution development, regardless of other parameter values. One interesting point of note in these results is in the location of the optimal parameter value combination, in particular that it does not exist at the most extreme for both parameters (i.e. bottom right hand corner). The optimal appears to be at the maximum number of connections (98), but with a mean edge strength of 0.6. This indicates the relationship between the two parameters is more complex than simply two positively correlated factors in revolution size. One possible reason for this is the effect of edge strength on the impact punishment has on individuals; stronger connections between individuals means the effect of punishment has on thresholds is increased, resulting in lower likelihood of revolution development. This works against the positive effect increased connection strength has on revolution development from the increased effect of being connected to someone who changes belief. This tension between the two associated effects is the likely cause for the optimal not existing at an extreme (i.e. 0.0 or 1.0).

5.3 Punishment and Control

The results for the impact of punishment and control are shown in figures 6, 7 and 8.

From figure 6, we can see that as the level of punishment increases, the proportion of the population with public beliefs “against” the authority decreases. As expected, punishment acts as an effective deterrent, reducing the number of agents who are publicly against the authority. This is largely due to the construction of the model, whereby agents increase their threshold proportional to the punishment level when an agent in their network is punished. This represents the idea of punishment discussed in [10], where it is used as a tool to maintain control through fear and intimidation. Interestingly, increasing the punishment level also leads to lower variance in the proportion of dissenting civilians, shown by the tighter confidence intervals. This suggests that along with reducing the number of publicly dissenting civilians, higher punishments lead to greater certainty in preventing social revolutions. As discussed earlier, revolutions have a bimodal behaviour, whereby if the number of agents with an “against” beliefs passes a critical number, a revolution tends to happen, and if it does not, the revolution quickly dies out. This suggests that increasing the punishment level quickly squashes any early signs of dissent, almost always preventing a revolution. Therefore, for a high punishment severity, we see low variance in the proportion of agents publicly “against” the authority. In contrast, when the punishment severity is low, the early stages of the revolution approaches the critical number of agents publicly “against” the authority, increasing both the mean proportion “against” and the variance of the results. The introduction of social media has resulted in constantly present activists, bloggers and journalists, leading to increased transparency of the actions of authority [9]. This could have two conflicting impacts on the severity of punishment. Firstly, it could hold central authorities more accountable for their actions, discouraging them from severe punishment due to the fear of public scrutiny. In this case, the results indicate that social revolutions would increase. Alternatively, it could lead to increased awareness of the punishments, increasing the civilians perceived severity of these punishments. This would have an equivalent effect to increasing the severity of punishments with respect to its intimidation factor. If this outweighs the first effect, then the proliferation of social media would likely decrease social revolutions. Ultimately, this is likely specific to individual societies and central authorities.

From figure 7 we can also see a downward sloping trend between the *punishment chance* and the mean proportion of agents publicly “against” the central authority. In the model, punishment chance reflects the probability that a dissenting agent is punished. If the agent is punished the other agents in the network become intimidated and less like to be publicly “against” the authority. As such, when the probability of punishment increases, as expected, we see a decrease in the mean proportion of agents with publicly displayed “against” beliefs. The *punishment chance* reflects the idea discussed in [9] and [10], whereby social media has led to better surveillance by central authorities. Consequently, the probability that they will detect and punish dissenting behaviour has increased. Therefore, the results indicate that social media could have negative impact of social revolutions, due to its increased assistance of authorities ability to detect dissidence and intimidate civilians. Again, we see that the confidence intervals become tighter as the *punishment chance* increases. As discussed prior, the bimodal nature of the revolutions leads to lower sensitivity towards extremes. In this case, with zero *punishment chance* we have an approximate 0.6 mean proportion publicly “against” the authority, which is not at either end of the extreme. In contrast, when there is a 100% *punishment chance*, the mean proportion publicly “against” is approximately zero, which is at an extreme and therefore has lower variance between runs.

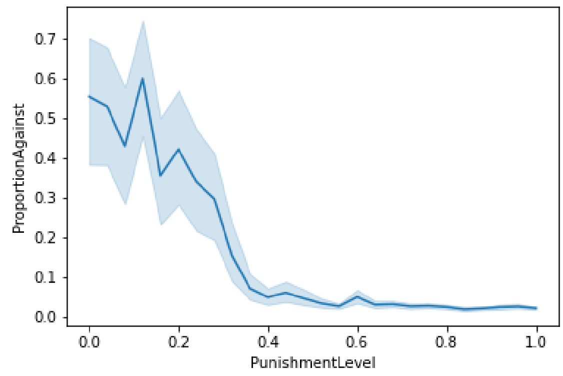


Figure 6: Mean proportion of the population with a public belief “against” the authority vs punishment severity. The light blue interval represents a 95% confidence interval.

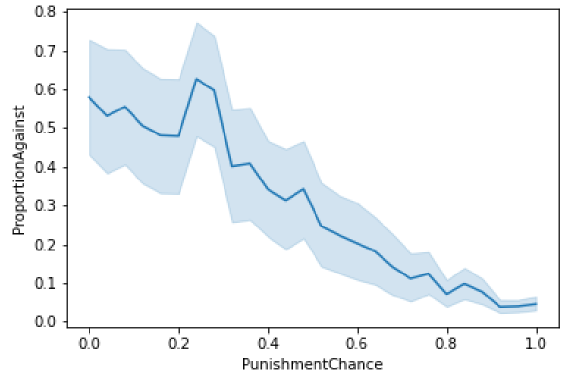


Figure 7: Mean proportion of the population with a public belief “against” the authority vs punishment probability. The light blue interval represents a 95% confidence interval.

Figure 8 demonstrates the combined effect of punishment severity and punishment probability. It demonstrates that a combination of high punishment probability and high severity of punishment is the most effective way to reduce the mean proportion of the population who join the revolution. This follows intuitively from the results seen in figures 6 and 7. It emphasises the overall effectiveness of fear and intimidation in controlling the population. Moreover, the dark region in the top-

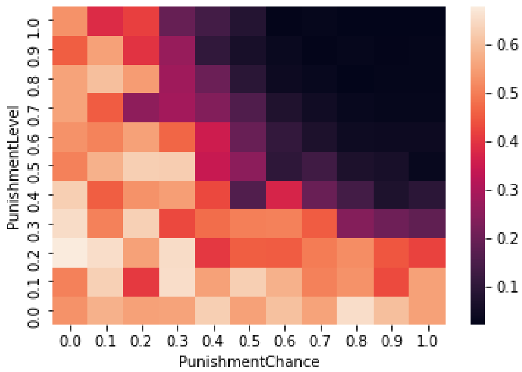
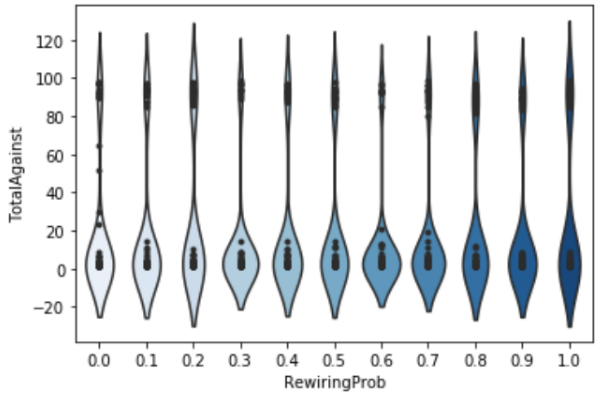
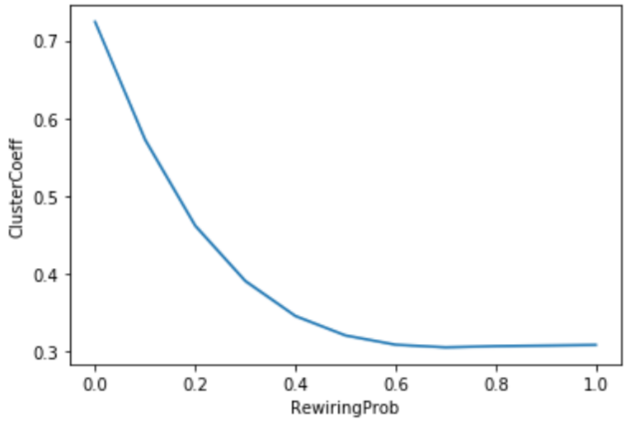


Figure 8: Joint effect of the punishment probability and punishment chance on the mean revolution size.



(a) Total agents publicly against at end of run vs. Rewiring probability



(b) Clustering coefficient of network as rewiring probability increases

Figure 9: Effect on the network of increasing the rewiring probability from 0 to 1.0.

right corner, denoting low proportions of the population who are publicly "against" the central authority, indicates that severe punishments requires good surveillance (and visa versa) to be effective in preventing revolutions. This makes intuitive sense, since surveillance is ineffective without punishment and punishment is ineffective without surveillance. When considering the impact of social media on this aspect of revolutions, it is likely that the increased surveillance has a significant increase in the central authorities ability to maintain control of the population. Even though, as noted prior, social media could either increase or decrease the severity of punishment, the increase in the surveillance moves us to a more rightward part of the heat-map, where the proportion of the population publicly "against" the central authority is low. This aligns with the discussion presented in [10], which indicate that social media has increased China's control of their population through enhanced surveillance.

5.4 Network Structure (Rewiring probability

The results for varying the network structure can be seen in 9. The bimodal nature of the revolution success is demonstrated once again, and remains consistent over all rewiring probabilities. The clustering coefficient of the network dips sharply as rewiring increases, as expected.

It was initially hypothesised that the proportion of successful revolutions would decrease as the network became less clustered and more randomised. As an example to demonstrate, a 'zero' who has publicly set their belief to 'against' may set off a 'one' that is their neighbour. In a highly clustered network, these two agents are more likely to share a mutual neighbour, increasing the likelihood of setting off more agents. However, as the rewiring probability increases, and the network becomes less clustered and more randomly structured, it was expected that two such agents would be less likely to set off a further revolt as they are unlikely to share neighbours.

This hypothesis was not borne out during experimentation, as the distribution of results over varying rewiring probabilities remains nearly identical, despite the decreasing clustering coefficient shown in 9. As such, for this model, the outputs are highly insensitive to changes in the rewiring probability, and there is no discernible difference in revolution likelihood between a highly localised network and a randomly connected network. It may be that the underlying distribution plays a dominating role over the rewiring probability, though further work is needed to test this.

6 Conclusion

This investigation lead to a number of insights into the effect of social media on social movement development. These are briefly summarised here:

1. A positive relationship was found between number of connections each individual has and social movement development. Based on relevant literature indicating social media has likely led to larger network sizes, this relationship may mean social media would have a positive effect on revolution development.

2. A positive relationship was found between mean edge strength between individuals and social movement development. Based on relevant literature indicating social media has likely lead to weaker average relationships, this trend may mean social media would have a negative effect on revolution development.

3. The relationship between number of connections and

mean edge strength is complex with the optimal setting being produced at mid-strength mean edge strength. Both variables were clearly found to require some baseline strength to facilitate revolutions which will have implications in a social media society based off the magnitude of influence social media has on these variables.

4. As expected, we found a negative relationship between the severity and probability of punishment with the mean revolution size, both individually and jointly. In context of the literature, social media likely increases the effectiveness of government surveillance, increasing the probability of punishment. Therefore, this would result in fewer revolutions. The effect of social media on the severity of punishment, and societies perception of the severity, is less clear in the literature. It could potentially decrease due to the greater accountability of authorities. This would contribute positively to social revolutions. Alternatively, the perception of the severity could increase due to the greater transparency. This would contribute negative to revolutions through fear and intimidation.

5. No relationship was found between the nature of the revolutions and the amount of rewiring done to decrease the clustering coefficient. This was unexpected as having many mutual neighbours was thought to increase the domino effect and produce more frequent social revolutions.

Importantly, we conducted the experiments by varying one or two parameters while holding the other parameters constant. This allows us to determine the effect of each of the discussed factors on social revolutions in isolation. For example, with this approach, we investigated the effect of punishment and control on revolutions, assuming that this was the only impact of social media. This approach has its of benefits, including the being able to observe the individual effects of each factor, and reducing the complexity of the model for both simulations and analysis. However, social media impacts all of these factors jointly. Therefore, they all likely contribute to social revolutions together, each with differing weights. Since the factors likely exhibit opposing impacts on social revolutions, the overall impact of social media is hard to determine from the experiments. Moreover, the body of literature suggests that the effect of social media on social revolutions may be either positive or negative [9]. This is due to the opposing effects of the differing factors. Therefore, it is hard to gauge which factors likely outweigh the others.

This investigation falls into a growing body of work related to the effect of social media on revolutions and, more broadly, the influence of social media on society. The implications of this work are somewhat limited and results largely confirm a number of expected trends relating to other research.

A number of strengths of our model and experimentation are outlined below:

1. **Simplicity**: Designing models, particularly when dealing with human behaviour, can often lead to growing complexity that can make models harder to use. Significant work went into getting the trade-off between complexity and simplicity right in this model. This model attempts to focus in on the important characteristics of revolutions and this is reflective in the final design.

2. **Novelty**: Modelling of social movements in this way, to the best of our knowledge, has not been done before.

3. **Subject matter**: Significance of social movements in the development of the societies around the world cannot be understated and contribution to the better understanding of this complex phenomenon is a worthwhile endeavour.

Various limitations were identified with the model and our analysis process:

1. **Lack of empirical data**: As stated previously, a number of the ideas that were being modelled were impossible to obtain empirical data for. This led to a number of assumptions about the likely nature of these amongst individuals in a society. This raised issues with the calibration and validation of the model.

2. **Diversity of research around social media**: Being a relatively new medium, there exists a wide variety of theories relating to the social effects of social media; it may also require more time before the effects are apparent. This does limit the conclusions drawn in this investigation.

3. **Size and homogeneity of community**: A small community size was chosen for simplicity and due to limited computational resources; this size, whilst unrealistic in relation to the types of societies being discussed, provided a large enough group for the ideas that were explored. Similarly, the homogeneity amongst individuals in the community (e.g. same #connections, same private belief etc.) is another likely unrealistic assumption.

In future work, the model could be extended in a number of ways to address various outlined limitations:

1. **Diversify private beliefs**: Societies are made up of individuals with a variety of opinions and varying levels of internal support for an idea would be interesting addition. This could be designating a portion of the population to have private beliefs against that of the social movement belief or moving away from a binary (*for* or *against*) support system to a continuous variable.

2. **Model conflicting belief systems**: Often there will be a pushback against revolutions within populations. One addition to the current model could be the inclusion of an anti-revolution movement that works similarly, but attempts to move people back to the traditional view. Modelling the dynamics between these movements could provide more realistic insights into social movement development.

3. **Joint impact of factors:** As mentioned previously, social media influences the factors considered in our experiment together, rather than in isolation. Future research could investigate the joint effect of these factors in order to gain a deeper understanding of the overall impact of social media on social revolutions.

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