A preliminary exploration into role of trust in information diffusion during a crisis.

Word count: 998

I. Introduction and Literature Review

The effective communication of relevant information is critical in raising public awareness and ensuring a coordinated response when a crisis occurs (Altay and Labonte, 2014; Comfort et al., 2016). Many crises, such as hurricanes and terrorist attacks, can be framed as ‘urgent diffusion’ events, in which information is quickly transmitted across a population to manage changing circumstances (p. 1, Rand et al., 2015).

Diffusion processes in social networks have been widely researched, as summarized by Borge-Holthoefer et al. (2013). Much past work has looked at the structural elements of networks and their impact on information diffusion, such as node centrality (Bakshy et al., 2011; Kitsak et al., 2010) and topology of connections (Cowan and Jonard, 2004; Rahmandad and Sterman, 2008). However, efforts that seek to integrate qualitative node or edge attributes into empirical research on information diffusion are less well-developed, particularly those that focus on implications for crisis communication.

We seek to address this gap by exploring the role of trust in information diffusion during a crisis. Trust in an information source is widely accepted to impact the likelihood of an individual adopting that information (Haynes et al., 2008; Hovland et al., 1953; Wu et al., 2017). Trust is thus particularly relevant during a crisis when crisis managers, such as government officials, may require the public to make rapid and widespread behaviour modifications (Reynolds and Quinn, 2008).

II. Research Question

Our research question in this work is as follows: *How does the trustworthiness of an information source impact the speed of information diffusion between individuals in a social network during a crisis?*

III. Methodology

We develop and deploy an agent-based model (ABM) to address this research question. ABMs are a well-established research tool for investigating the dynamics of information diffusion as they are able to account for dynamic interactions between heterogeneous agents (as in, Altay and Pal, 2014; Chen, 2019; Rand et al., 2015). Our ABM is developed based on a preferential attachment network topology (Barabási and Albert, 1999), as exemplified by Figure 1. This model operates in a manner derived from the Independent Cascade model of information diffusion (Goldenberg et al., 2001), following Rand et al. (2015).

Implementation of the model in Netlogo (Wilensky, 1999) was aided by Rand (2019a, 2019b, 2019c) and further details are provided in the model’s ODD description (Grimm et al., 2010).

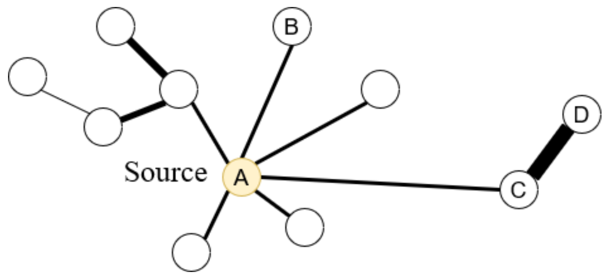


Figure 1. *Sample preferential attachment network, whereby Node A is the information source, and all other nodes correspond to information-seeking individuals. Weight of links corresponds to the level of trust between two nodes.*

We collect data to answer our research question by running our model with varying trust coefficients between the source node and all its neighbours (eg. between Node A and Node B). We run experiments with trust coefficients set from 0.05 to 1.00, incrementing by 0.05. We repeat each run 60 times to control for stochasticity in the model. For each timestep for each run, we collect data on the total number of agents that have adopted the information and the number of new agents that have adopted the information. Our results are primarily based on a network with 1000 nodes, however we also run similar experiments with 100 and 500 nodes to test the sensitivity of our model to population size.

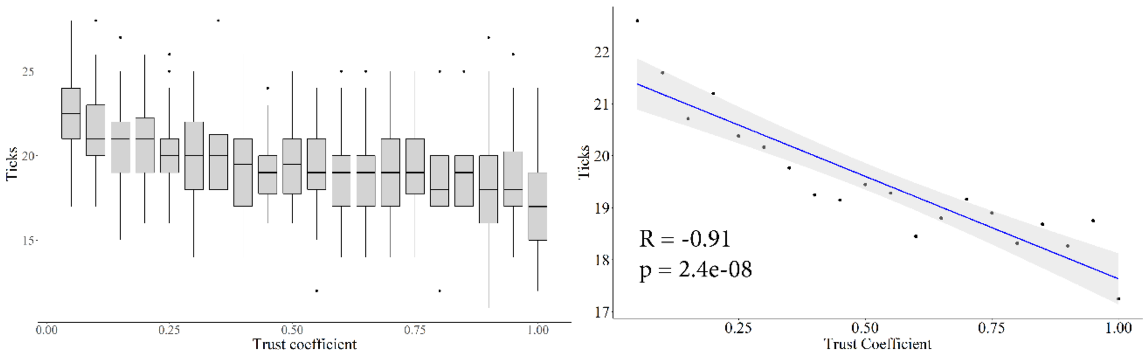
IV. Results and Discussion

As shown in Figure 2, greater trust in a source has a significant negative linear relationship (at the $p<0.05$ level) with the speed with which 50% of the network has adopted the information. However, we see that different levels of trust have little relationship to the speed at which 100% adoption is reached. This finding supports the work of Altay and Pal (2014) who conclude that more rapid trust-building in a source does not relate to better information diffusion. Due to the stochastic elements of our model, we also see notable variance in the data collected for each repetition of our model.

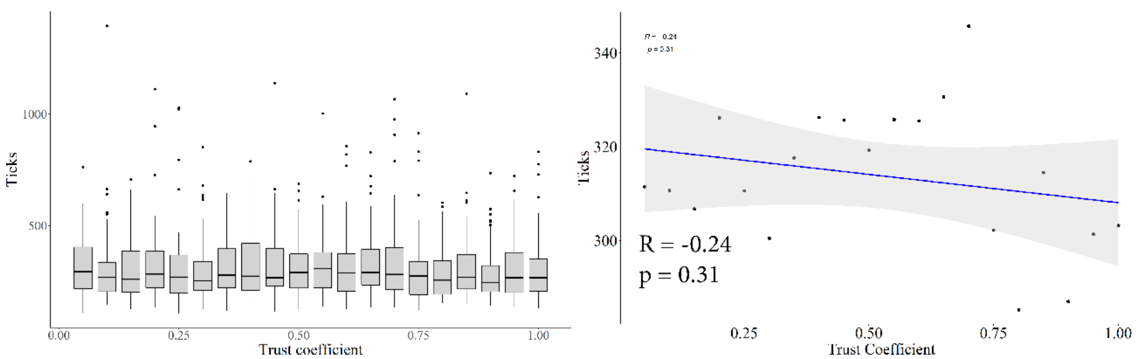
Figure 3 illustrates how a greater trust coefficient is linked to a steeper initial peak in the number of agents who have newly adopted the information. Following approximately 20 ticks, all trust coefficients show a roughly uniform pattern in the number of agents who newly adopt the information at each time step.

We presume that the underlying preferential attachment network structure has a notable impact on our findings. The peaks shown in Figure 3 for greater trust coefficients likely correspond to the quick adoption of information from the source’s large number of direct neighbours. Agents who are not connected to the initial source may take longer to adopt information if they do not trust their network neighbours. We see that the initial peak in adoption from a more trusted source does not correspond to faster overall diffusion in the network, highlighting potential differences between localized and network-wide diffusion dynamics. Future efforts may expand on this work by exploring the impact of different network structures in this model.

We acknowledge that our model does not account for situations in which an individual may decide to reject the information adopted by their neighbours or adopt information from a competing source. As such, this model is not well-suited to the diffusion of controversial information, which may be more likely to be rejected by some individuals. Rather, our model is more appropriate for factual information that will be adopted with sufficient sustained exposure.



A: 50% adoption



B: 100% adoption

Figure 2. *Trends in the number of model ticks to reach 50% and 100% adoption in the 1000 agent network across different levels of source trust. The **left graphs** show the distribution of points from all 60 repetitions and the **right graphs** show the mean value across repetitions. R values correspond to the Pearson correlation coefficient.*

Table 1*. Pearson correlation coefficients for the relationship between number of model ticks to reach 50% and 100% adoption and source trust coefficient values for varying network sizes.*

	100 agents	**500 agents**	**1000 agents**
50% adoption	-0.90 **	-0.93**	-0.93**
100% adoption	-0.16	-0.55*	-0.24

** p<0.001, * p<0.05

Table 1 includes the primary results from Figure 2 and suggests that different population sizes give similar results, although the significance of the correlation for 500 agents at 100% adoption may be worth exploring in subsequent work.

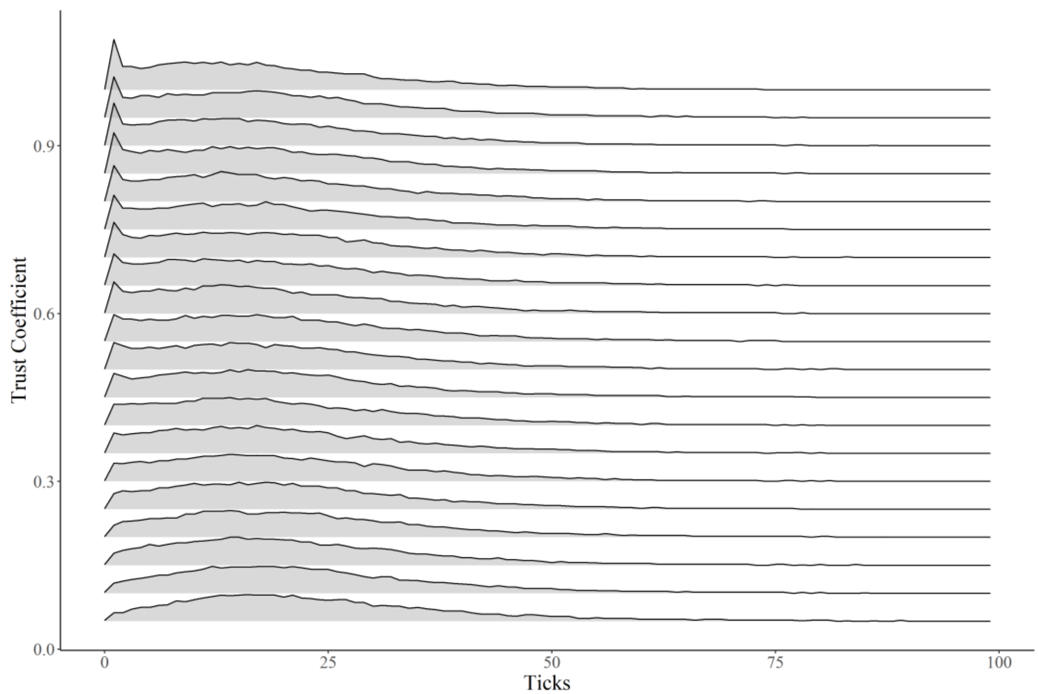


Figure 3. *Comparative volume of newly aware agents for varying levels of trust up to 100 ticks in simulations with 1000 agents. Values reflect the median across all 60 repetitions.*

V. Conclusion

Our work has investigated how trust in an information source impacts the speed of information diffusion in a social network during a crisis. Using an ABM, we find that greater trust in a source corresponds to significantly faster information diffusion across 50% of individuals in a network, but not 100% of individuals. These findings have implications for crisis communications strategies, suggesting that efforts to increase trust in a source are, alone, not an effective strategy for reaching all individuals in a network with greater speed.

VI. References:

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