False Claims Hurt: Examining Perceptions of Misinformation Harms during Black Lives Matter Movement

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[Extended Abstract]

I. Introduction and Background

In our interconnected big data world, daily enormous amounts of information are generated, transferred and interpreted. Numerous malicious Internet users have generated and circulated fake news and misleading information, poisoning the information environment (Tsfati et al., 2020). Such misinformation can lead to serious damages or harms, ranging from physical harms, psychological harms, reputational harms, social harms, safety harms, or confusion harms (Tran et al., 2020). Facing such situations, to the best of our knowledge, there are barely any studies that systematically examine people's perceptions about possible harms from misinformation.

This paper adapts 15 defined misinformation harms in the context of humanitarian crises (Tran et al., 2020) and drawing on the concept of Big Data 3Vs which focus on value, volume and velocity of the harms (Anuradha, 2015), it examines perceptions of misinformation harms for a recent crisis context that has gained serious public attention, the Black Lives Matter movement in 2020. The movement has yielded severe consequences to numerous victims and communities (Gibson et al., 2020). In this context, we extract three misinformation scenarios related to the crisis. By analyzing differences of perceived misinformation harms of those scenarios, we find in interesting patterns of misinformation harms. Findings can contribute to the literature of knowledge about misinformation harms and can also be used to help derive appropriate action plans for involved stakeholders facing such crisis misinformation scenarios.

II. Methodology

Drawing from prior studies, we developed a survey that was composed of questions about 11 defined misinformation harms applicable to crisis misinformation scenarios (Tran et al., 2020) as well as questions based on Big Data 3Vs to capture different perspectives of misinformation harms (Anuradha, 2015).

The defined harms are called "component harms" in this paper. Component harms involve various physical harms (such as life threatening, injury or income harms), psychological harms (such as emotion, trust or confusion harms) and complex harms as the combinations of both physical and psychological harms (such as connection, isolation, decision, privacy or discrimination harms). They are captured in terms of two dimensions, i.e., the likelihood of occurrence and level of impacts.

The 3V levels are derived from Big Data 3Vs. These are obtained by using a set of questions that asked participants to rate the value (or severity of harms), volume (or probability that people face victimization), and velocity (or the speed of spreading the misinformation to cause harms).

We recruited 114 participants from the crowdsourcing channel Amazon Mechanical Turk (http://mturk.com) that live in the United States and were more than 18 years old.

Three misinformation scenarios related to the movement were chosen for the survey design and are summarized in Table 1. All scenarios were disseminated by different social media platforms and were debunked as misinformation by multiple fact checkers including PolitiFact and Snopes.

Table 1: Chosen scenarios related to Black Lives Matter movement

Code	Scenario names	Scenario description	Citation
S1	Fake death.	Mr. Floyd is not dead, and he and officer Chauvin are stage actors.	Alba, 2020.

S2	George Soros.	Mr. George Soros, a billionaire, sponsored the protests and riots across the U.S related to Mr. Floyd's death.	Alba, 2020.
S3	Antifa.	Antifa is blamed as "a terrorist organization" that fuels riots and looting, and that antifa activists must take responsible for political and financial damage.	Alba, 2020.

III. Data analyses

1. Plotting component harms in different scenarios

Component harms are plotted and presented in Figure 1 based on the two dimensions of Likelihood and Impacts. We detected several differences between harms based on scenarios.

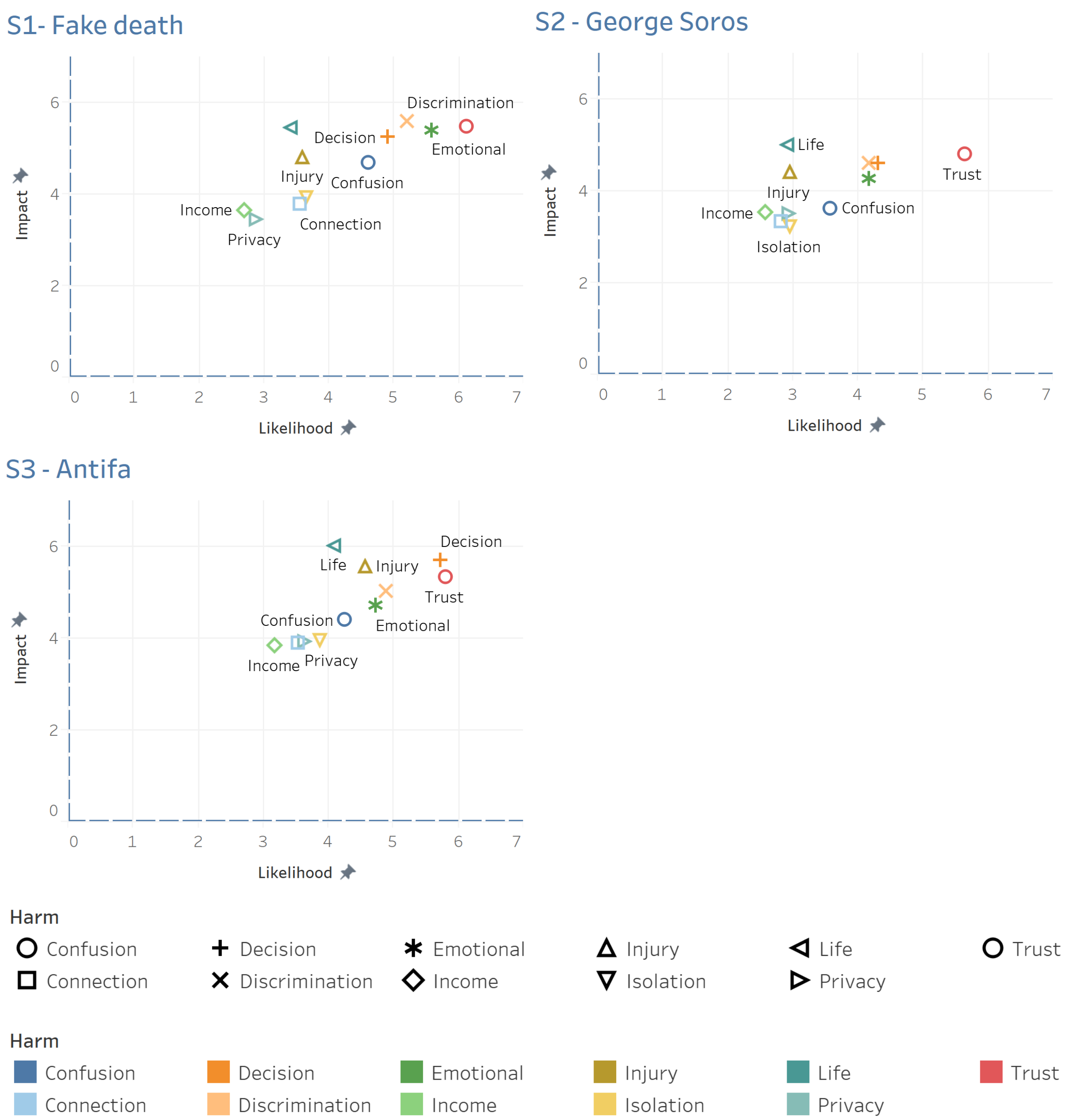

Figure 1: Component harms based on scenarios.

2. Examining 3V levels of scenarios

We grouped three questions regarding 3V levels (in other words, severity, victimization and spreading speed) by using principle component analysis (Wang et al., 2015). Results of the factor scores are shown in Table 2, which is classified as low, high and medium 3V.

Table 2: 3V scores of three scenarios

Scenario	Scenario name	3V average	3V standard deviation	Classification
S1	Fake death	0.037	1.099	Medium
S2	George Soros	-0.321	0.956	Low
S3	Antifa	0.284	0.842	High

After that, we performed post hoc analyses to detect significant differences between pairwise comparisons of the average values of 3V using Tukey test (Howell, 2010). S2 and S1 were significantly different (p-value = 0.016) and so were S2 and S3 (p-value = 0.000) while there was no significant difference between values of S1 and S3 (p-value = 0.133).

3. Examining component harms of scenarios

In this task, we aggregated all likelihood scores and impact scores of 11 component harms into single scores of harm likelihood and harm impact. Then, we use pairwise t-tests to examine differences between scenarios' harm likelihood and harm impact scores. Results are shown in Table 3 for all six pairs.

Table 2: 3V scores of three scenarios

Pairs	P-value	Low value	High value
1. S1 – likelihood and S2 – likelihood	0.000	S2 = 3.5558	S1 = 4.2073
2. S2 – likelihood and S3 - likelihood	0.000	S2 = 3.5558	S = 4.3923
3. S1 – likelihood and S3 - likelihood	0.204	NS	NS
4. S1 – impact and S2 – impact	0.000	S2 = 4.0742	S1 = 4.6738
5. S2 – impact and S3 – impact	0.000	S2 = 4.0742	S3 = 4.7616
6. S1 – impact and S3 - impact	0.574	NS	NS

Note: S1 – fake death; S2 – George Soros; S3 – Antifa. NS: not significant.

IV. Discussion and conclusion

During humanitarian crises, misinformation can be widespread and cause serious consequences or harms. Research related to misinformation harms are scarce. Our study examines different types of perceived misinformation harms and 3V scores of three specific scenarios that are tied to a recent and well-known humanitarian crises, the Black Lives Matter movement in 2020.

The patterns of harms in the three considered scenarios are consistent. At first, as a scenario related to personal involvement of a billionaire to the movement, S2 has negative and lowest scores of 3V while the false claims related to the source of the movement (S1 – fake death) and a type of terrorism act (S3 – Antifa) yielded positive and much higher 3V scores. Then, based on perceived component misinformation harms, S1 and S3 have no significant difference on both likelihood and impacts while S1-S2 and S2-S3 pairs have very significant differences of both likelihood and impacts. This finding is very consistent with scenario-level analyses of 3V scores. In addition, S2 always have much lower values in all scenarios of both mean likelihood and impact scores. All of these findings are very consistent with the very first comparison of scenario-based 3V scores, and we got evidence that derived 3V scores tend to correlate with perceived likelihood and impact of component harms in all scenarios.

Such a finding of consistent patterns between two different aspects of misinformation harms measured in two different ways contributes to existing literature of misinformation understandings and suggest similar research replications in the future. The finding can also support involved stakeholders such as local government's agencies dealing with the Black Lives Matter protest to better predict the perceived harms from misinformation based on estimating 3V scores of the claims, which help prioritize and optimize the use of limited resources in such crisis.

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