

C. RQ3: Discussion Topics

The analysis from longitudinal topic modelling for 3 months of tweets related to COVID-19 has proven to be effective in identifying key trends of public dialogue and could potentially be used to guide targeted and timely interventions. For example, the overall trend of topics started off containing words with negative connotations such as “violence”, “assault”, “marginalize”, with the topics suggesting the woes and frustrations associated with the COVID-19 lockdown/quarantine. However, as time went by, the topics started shifting towards the more positive end of the spectrum, with topics that involved tweets about keeping productive during the lockdown and tweets about approaching a “new normal” with telecommuting and e-commerce. This signals a potential “glimmer of hope” amidst the bleak outlook because it shows that society is accelerating the use of technology, progressing forward in becoming “smart” cities, and adapting to the new future.

IV. CONCLUSION

In this paper, we present a framework that allows the general public or public health officials, to understand the public sentiment towards the pandemic, the key topics discussed. For example, with an idea of what the key topics are at a specific time in point, as well as across time, the general public can be educated about events that might not have been reported that widely in their specific countries. Using this framework, we studied three research questions relating to COVID-19, namely: (i) how sentiments/emotions change during the pandemic? (ii) how sentiments/emotions change in relation to global events? and (iii) what are the common topics discussed during the pandemic?. We believe that this research’s methodology can be easily tweaked and applied to different contexts as well to examine other research topics such as that of a natural disaster or political events.

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