Supplementary Information

A game theoretic complex network model to estimate the epidemic threshold under individual vaccination behaviour and adaptive social connections

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S1 Description of the empirical network

For the empirical network generation, we utilized a dataset sourced from a survey conducted in a rural village in southern Karnataka, India, as part of a broader study encompassing 75 villages [1]. The survey involved a household census, with a subset of individuals providing detailed information on their social relationships within the village. This data served as the basis for constructing network graphs for each village included in this study. Additionally, comprehensive household and individual information is provided. The selection of these villages was informed by Bharatha Swamukti Samsthe (BSS), a microfinance institution, which identified them as potential locations for its operations. BSS began expanding into these villages six months post-survey, ultimately extending to 43 within two years. Household participation in BSS's microfinance program was recorded and matched with the household census data. Approximately half of the households received detailed surveys wherein individuals listed their relational connections. The household stratification by geographic subregion and religion was achieved through random sampling. The resulting networks are undirected and symmetric, with each matrix row or column representing an individual. While the matrices lack explicit headers, files within the "adjacency matrix keys" folder provide linkage between rows (or columns) and specific individuals or households. The empirical network for one southern village [2] was constructed using the igraph-python package [3], resulting in 1180 nodes and 4626 edges. The degree distribution plot of this empirical network is depicted in Figure S1.

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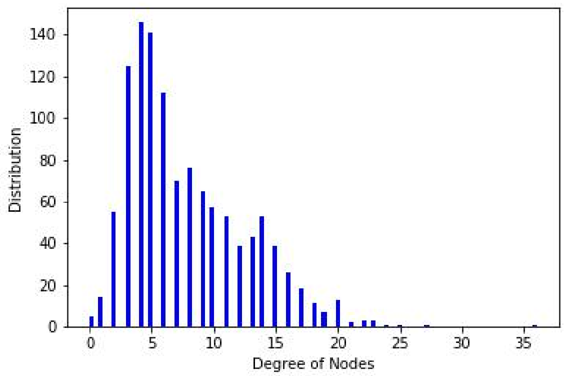

Figure S1: Figure shows degree distribution of one of the southern villages as described above.

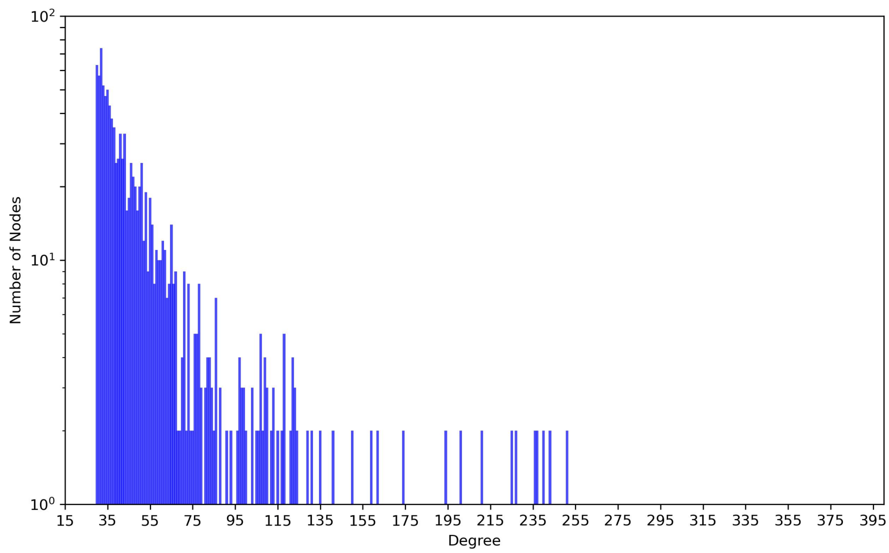

Figure S2: Figure shows the degree distribution of virtual scale-free network for 1180 nodes.

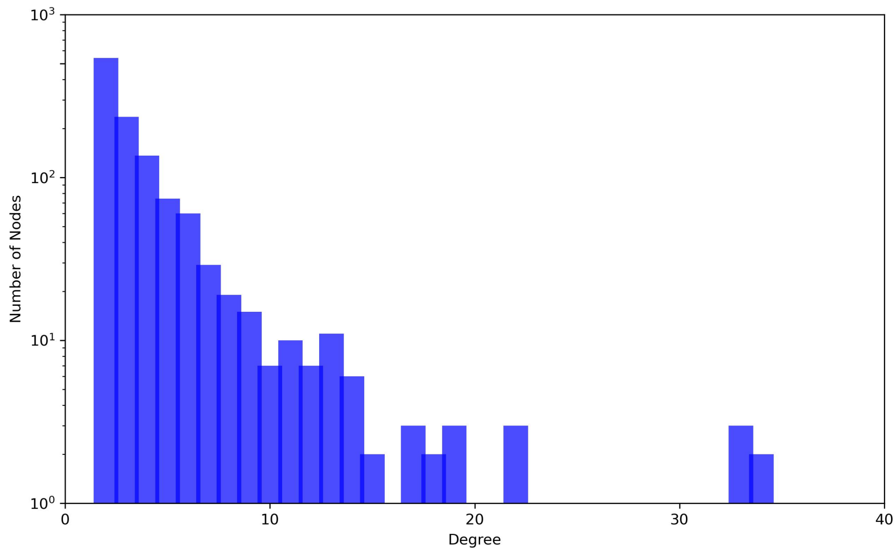

Figure S3: Figure shows the degree distribution of physical scale-free network for 1180 nodes.

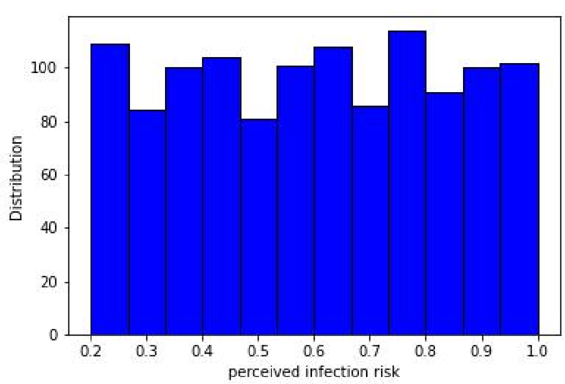

Figure S4: Figure shows the histogram plot of the initial perceived infection cost for 1180 nodes.

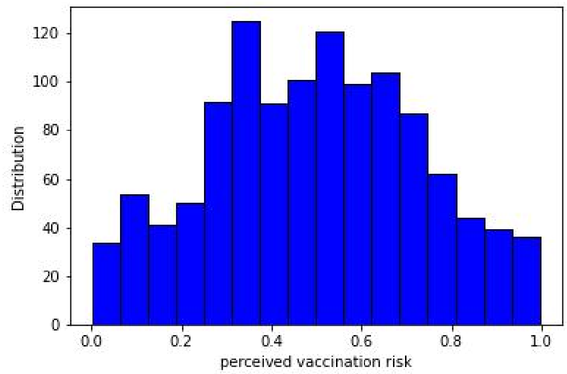

Figure S5: Figure shows the histogram plot of the initial perceived vaccine cost for 1180 nodes.

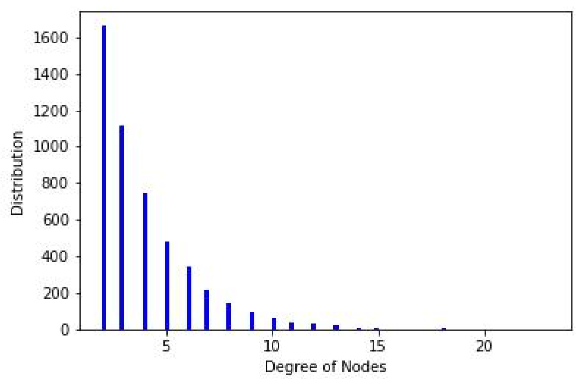

Figure S6: Figure shows degree distribution of physical scale-free network for power-law exponent $(\alpha) = 0$.

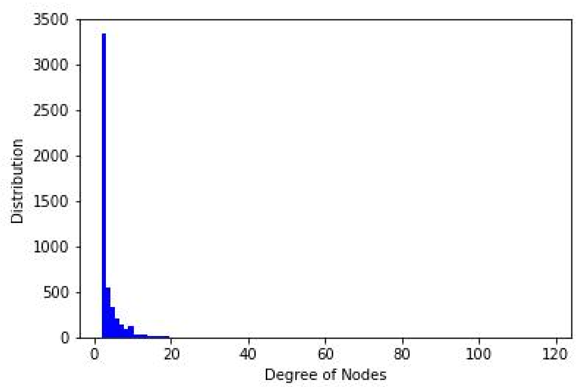

Figure S7: Figure shows degree distribution of physical scale-free network for power-law exponent $(\alpha) = 1$.

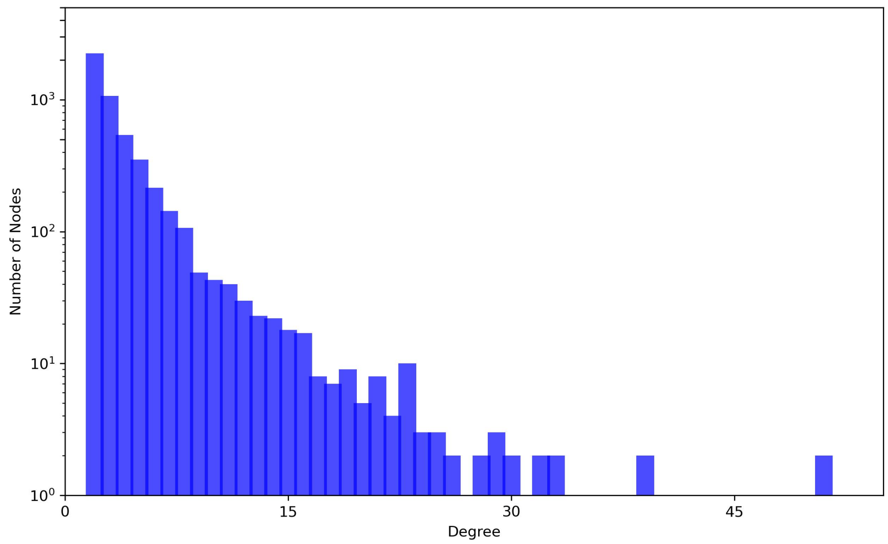

Figure S8: Figure shows degree distribution of physical scale-free network for power-law exponent $(\alpha) = 2$.

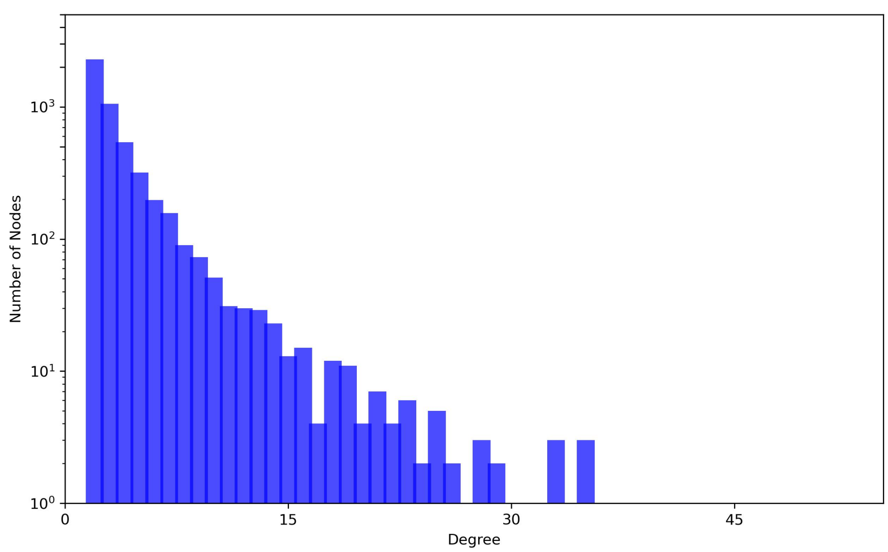

Figure S9: Figure shows degree distribution of physical scale-free network for power-law exponent $(\alpha) = 3$.

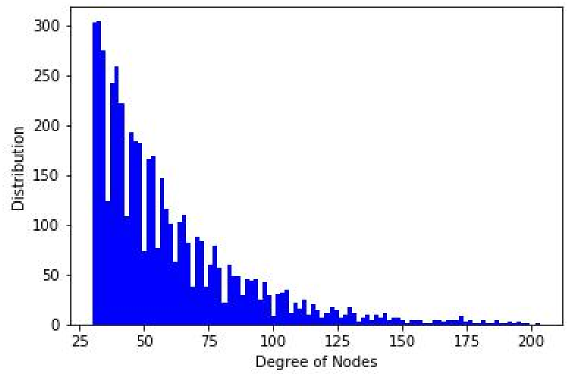

Figure S10: Figure shows degree distribution of virtual scale-free network for power-law exponent $(\alpha) = 0$.

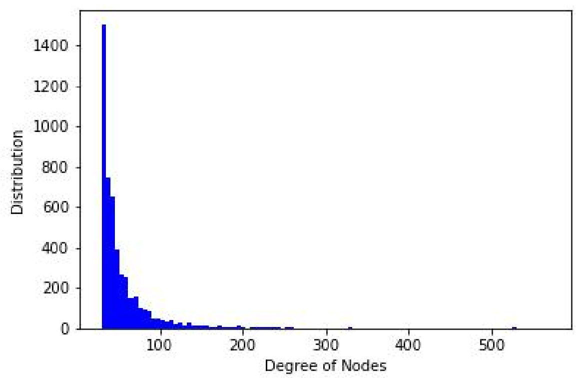

Figure S11: Figure shows degree distribution of virtual scale-free network for power-law exponent $(\alpha) = 1$.

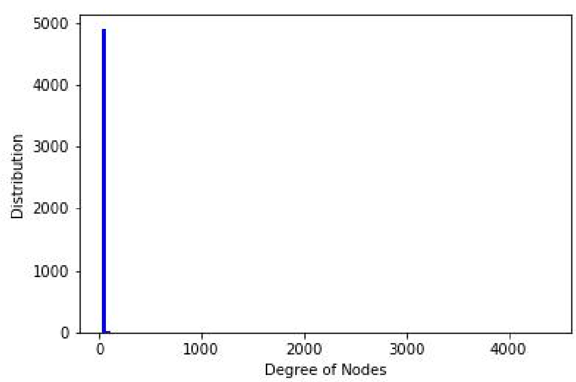

Figure S12: Figure shows degree distribution of virtual scale-free network for power-law exponent $(\alpha) = 2$.

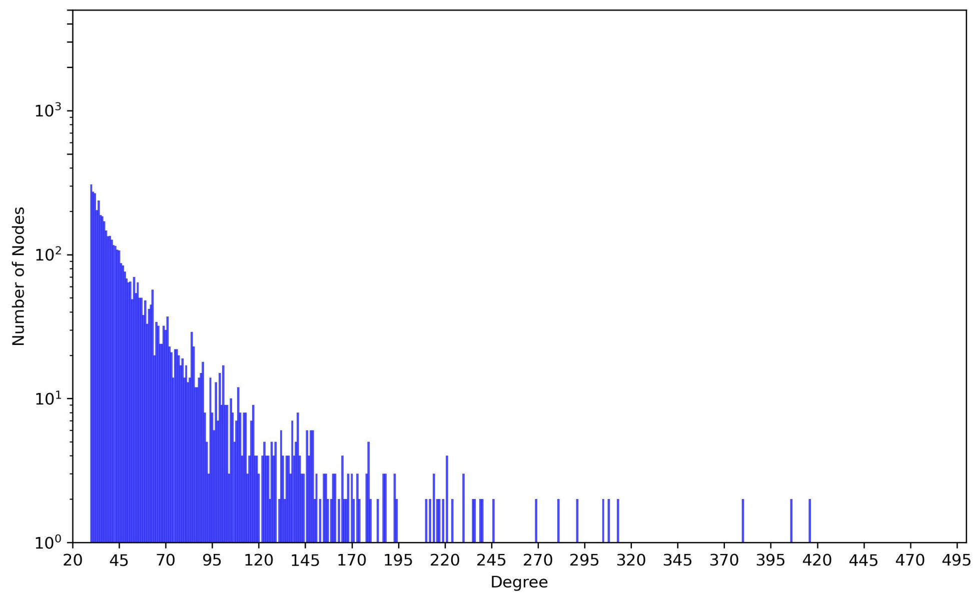

Figure S13: Figure shows degree distribution of virtual scale-free network for power-law exponent $(\alpha) = 3$.

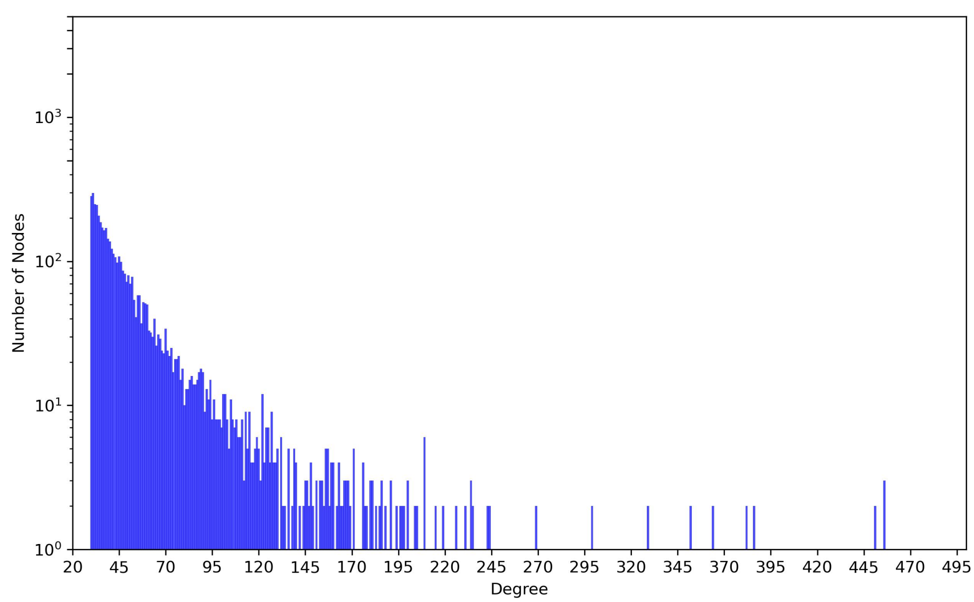

Figure S14: Figure shows degree distribution of virtual scale-free network for power-law exponent $(\alpha) = 2.3$.

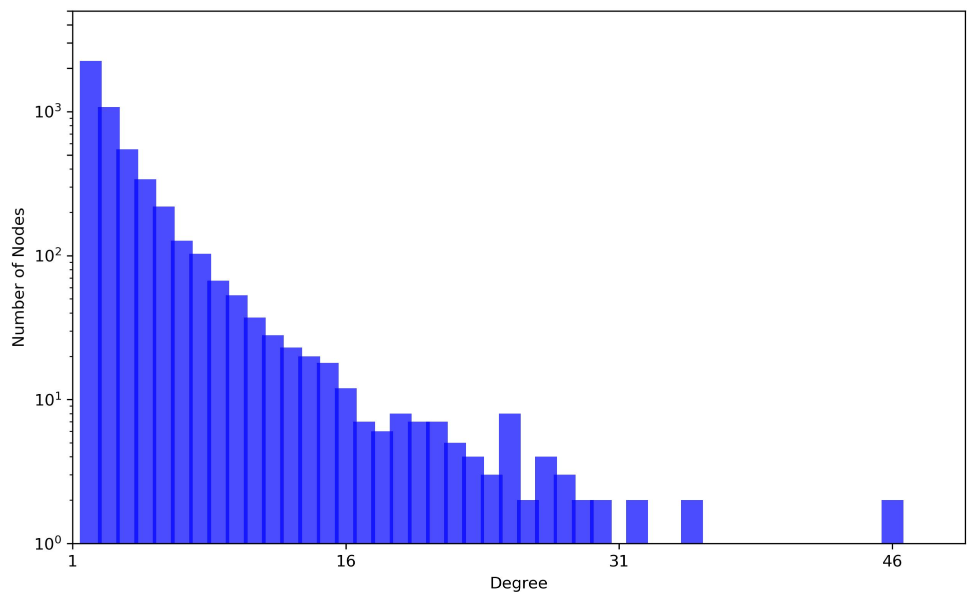

Figure S15: Figure shows degree distribution of physical scale-free network for power-law exponent (α) = 2.3.

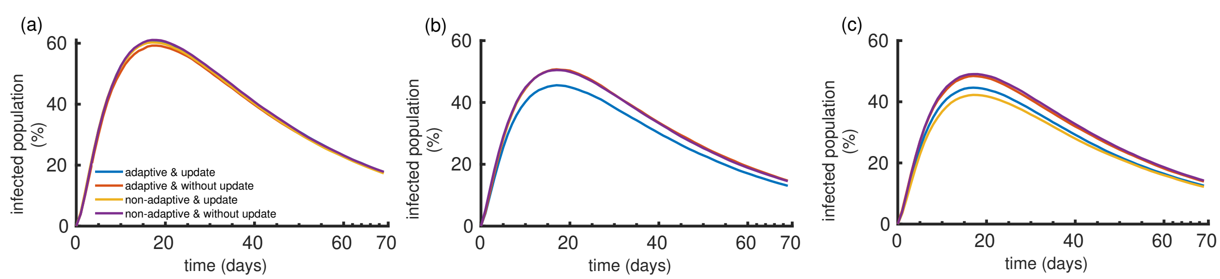

Figure S16: Figure shows (a) infected population (%) for $\theta_j = 0$; (b) infected population (%) for $\theta_j = \zeta[1 - e^{-\varkappa N^j_{nv}}]$; (c) infected population (%) for $\theta_j = 1$; for different model scenarios. Each point on the plot is an average of 50 simulations.

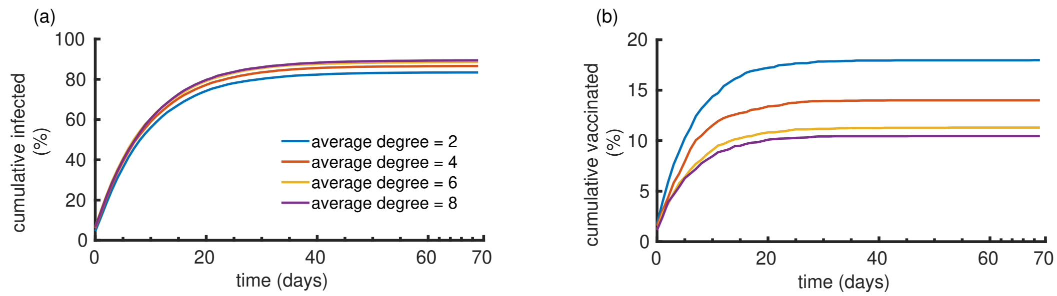

Figure S17: Figure shows (a) cumulative infected population (%); (b) cumulative vaccinated population (%); for various average number of physical connections. Each point on the plot is an average of 50 simulations.

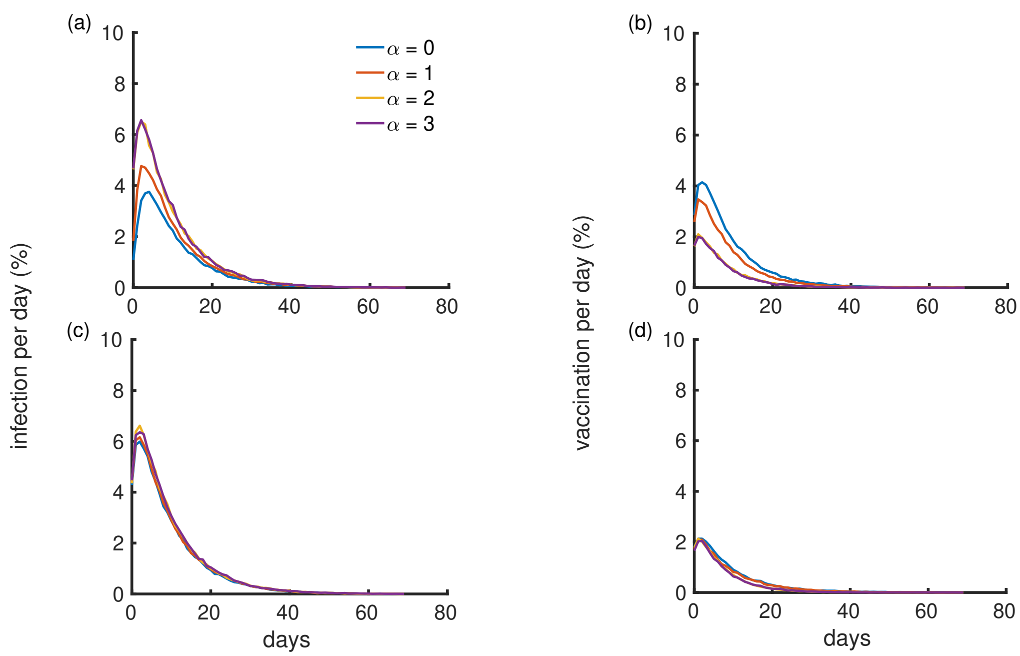

Figure S18: Figure shows (a) infected population per day (%); (b) vaccinated population per day (%); for different values of power-law exponent (α) in the physical network. (c) infected population per day (%); (d) vaccinated population per day (%); for different values of power-law exponent (α) in the virtual network. Each point on the plot is an average of 50 simulations.

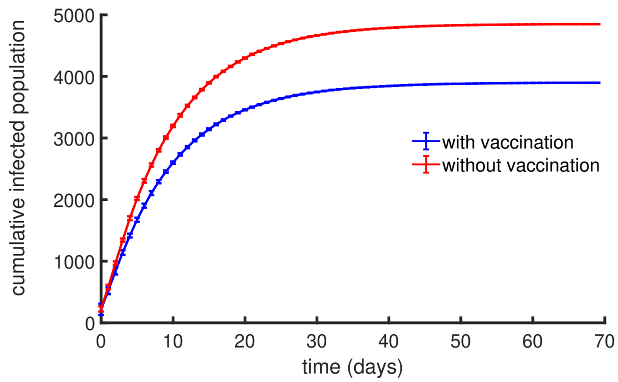

Figure S19: Figure shows the final size of the cumulative infected population with vaccination and without the vaccination dynamics in the physical layer. Each point on the plot is an average of 50 simulations.

References

[1] Abhijit Banerjee, Arun G Chandrasekhar, Esther Duflo, and Matthew O Jackson. The diffusion of microfinance. *Science*, 341(6144):1236498, 2013.

[2] Anupama Sharma, Shakti N Menon, V Sasidevan, and Sitabhra Sinha. Epidemic prevalence information on social networks can mediate emergent collective outcomes in voluntary vaccine schemes. *PLoS computational biology*, 15(5):e1006977, 2019.

[3] Gabor Csardi, Tamas Nepusz, et al. The igraph software package for complex network research. *InterJournal, complex systems*, 1695(5):1–9, 2006.