Applying Diffusion of Innovations Theory to Social Networks to Understand the Stages of Adoption in Connective Action Campaigns

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Abstract

This research proposes a conceptual framework and computational method for determining when technology-equipped crowd networks act together under connective action. The experimental approach taken in this study builds on the diffusion of innovations theory, critical mass theory, and previous s-shaped production function research to provide ideas for modeling future connective action campaigns. Most social science research on connective action has taken a qualitative approach. There are limited quantitative studies, but most focus on statistical validation of the qualitative approach, such as surveys, or only focus on one aspect of connective action. In this study, we extend the social science research on connective action theory by applying a mixed-method computational analysis to examine the affordances and features offered through online social networks (OSNs) and then present a new method to quantify the emergence of these action networks. Using the s-curves revealed through plotting the information campaigns usage, we apply a diffusion of innovations lens to the analysis to categorize users into different stages of adoption of information campaigns. We then categorize the users in each campaign by examining their affordance and interdependence relationships by assigning retweets, mentions, and original tweets to the type of relationship they exhibit. The contribution of this analysis provides a foundation for mathematical characterization of connective action signatures, and further, offers policymakers insights about campaigns as they evolve. To evaluate our framework, we present a comprehensive analysis of COVID-19 Twitter data. Establishing this theoretical framework will help researchers develop predictive models to more accurately model campaign dynamics.

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1 Introduction

Extensive quantitative research has been conducted within social media over the past several years, however research in the areas of digitally enabled collective action is relatively new. The field of computational social science has also grown tremendously. Online Social Networks (OSNs) afford users greater opportunities to participate in collective action. These platforms also provide a method to coordinate and influence behavior. The type of collective action coordinated using digital technologies is referred to as connective action. Connective action is a result of changes to the information environment that affect the way that citizens seek and find political information. OSNs impact the nature of the information that users receive and reduce the costs of interacting with each other. Digital technologies are not, however, the only property of connective action. The coordination must be either self-organized or lack formal organizational structure. In this study we assess the formation of these cyber collective communities and analyze interactions between actors and identify how they influence their communities.

Contemporary protests and social movements have been identified as using different styles of organization and communication known as connective action [Toepfl, 2018]. These types of protests and movements are primarily focused on: 1) individual preferences and 2) mobilization through personal communication. The key to understanding connective action campaigns is identifying the types of affordances used by users, as well as understanding the interdependencies among users. The S-shaped signatures identified in connective action events provide insights into past social science theories, such as Diffusion of Innovations theory, that support characterizing these events through a quantitative approach. The S-curve characteristics can be used to model an emerging event and to identify an information campaign while it is in its accelerating phase prior to reaching critical mass.

In this paper, we examine connective action through the lens of information diffusion by looking at the event signatures of social media campaigns related to the COVID-19 pandemic. A study of Twitter data surrounding the use of nine COVID-19 related hashtags reveals s-shaped diffusion curves that show the rate at which information spreads throughout the life cycle of the nine corresponding misinformation campaigns. The s-shaped phenomenon is strikingly similar to discussions from diffusion of innovations (DOI) theory [Trott, 2018] that characterize how new ideas and technology spread over time in terms of their rate of adoption among users. We also consider this s-shape as a production function as discussed in critical mass theory [Priestley, 2020]. Our work extends previous contributions by comparing observations from our social network analysis, epidemiological studies, and connective action framework and comparing these from the perspectives of DOI and s-curve socio-technical theories. Together, the mathematical properties of the DOI and s-curve functions and our observations from a social networking perspective form a bridge to help guide our research toward developing a predictive model for detecting connective action campaigns. Transferring knowledge from these thoroughly established theories to the connective action domain also allows us to apply this technique across different social media platforms. Two main contributions of this study are (1) using DOI theory to identify s-curve characteristics and using those characteristics to model an emerging connective action campaign, and (2) using an examination of the affordances and interdependencies associated with the connective action to distinguish the types of campaigns. Obtaining a firm understanding of this affordance-interdependence relationship will help researchers and policymakers determine the type of countermeasures to properly respond to the type of campaign.

The information campaigns where s-shaped phenomenon is observed are consistent with the concept of diffusions of innovation. The stages that influence the adoption of an innovation or idea can also be used to describe the factors that influence the adoption of connective action (mis)information campaigns. To influence rapid adoption, connective action campaigns use affordances through online social networks while reducing costs to join and providing anonymity. Since the costs to join a campaign are low, the decision to adopt the idea, or join the movement requires little exposure or risk to the user. As part of our analysis, we analyzed 72,393 Tweets for popular COVID-19 discourse and anti-lockdown protests that occurred throughout 2020. We analyze the input features used in these connective action campaigns and show how these features follow the s-curve function, which allows us to characterize them mathematically. Observing the message frequency plot helps us to understand where an event is in its adoption cycle. Some events have a flash mob style startup feature where they start quickly and then quickly disperse, while others take longer to get started and to become adopted. Additionally, some events combine these two approaches where the action slowly starts, quickly accelerates, then slowly decreases. This is the s-curve pattern we observe and discuss in this work. These s-curve patterns can be observed in their production function curves described in collective action of critical mass theory.

Two fundamental research questions are studied:

> RQ1: Can we apply proposed affordance-interdependence relationships to offer a view of how an information campaign unfolds?
>
> RQ2: Can we leverage existing social science theories on diffusion of information to provide background for a mathematical representation of these information campaign adoption rates?

The remainder of this paper is presented as follows. Section 2 provides a comprehensive review of the social science theories we use to compare to our connective action models. In section 3, we provide our approach to data collection and processing of the data. Next, we discuss the roles of the affordance-interdependence relationships in section 4 and how they describe certain events. We conclude with section 5 discussing our findings and future work to this line of research.

2 Literature Review

The observational approach taken in this study builds on the diffusion of innovations theory, critical mass theory, and previous s-shaped production function research to provide ideas for modeling future connective action campaigns. We draw upon well-established social science theories to provide theoretical grounding for our computational framework around connective action. Our socio-technical approach applies quantitative methods to measure the social processes that drive users to interact with each other on social media. In this section we will provide background information on some of these previously studied social science disciplines.

Connective action is a form of collective action where users form more individualized and more technologically organized actions around a protest, demonstration, or social movement. The actions resulting from individualized organization results in informal, but locally organized communities without the need for collective identity framing and formally coordinated organization. Lance Bennett first defined connective action in his work, The Logic of Connective Action (Bennet, et al., 2012), where he identified digital communication as an organizational process for mobilizations. Bennett also describes the role of individuals as the driving force behind connective action. The connective action principles can be summarized as collective identity, network organization, and mobilization of resources. In this paper we touch on network organization, but primarily focus on the mobilization aspect of the work.

Social media enables these types of networks to organize and emerge quickly, but often lack the leadership and direction needed to ensure long-term policy change [Margetts, 2015]. When we consider how users are mobilized into an information network, we can examine how they are exposed to the information through user affordances. Ahuja et al. [2018] examined the context of digital activism from the perspective of collective action concepts. Their work primarily focused on the concepts of affordance, network building, and synthesis. Digital activism is often achieved by using the concept of digital affordances for the collective purposes of network building and synthesis, as suggested by mobilization theory. [Ibid]. Alfonzo [2021] examined digitally networked action (DNA) to examine the repeated patterns of communication and "digital actions" on Twitter during Black Lives Matter (BLM) protests. The author analyzed the tweet streams of 184 BLM activists and concluded that they fell into four categories: 1) Personal Action Frame Sharing (PAFS), which told stories filled with emotion such as anger, exhaust, confusion, hope, etc.; 2) Bottom-Up Information Sharing (BUIS), which were a form of grassroots news reporting, media link sharing and citizen journalism; 3) Democratic Ideals (DI) which criticized the media for what the activists perceived to be minimal or biased reporting; and 4) Self-Selected Community Action (SSCA), which were calls to action (CTA) and the sharing of skills/resources. The SSCA tweets often included well-organized CTAs asking people to spread information, attend events, boycott, sign online petitions, put pressure on leaders, etc. The author stated that all the tweet streams used Twitter engagement affordances such as retweets, the use of hashtags, the use of handles to make mentions, and the use of links. The author concludes that collective identity building took place via earnest communication and story sharing, and that tweets that helped to identify "friend/enemy subject positions" served to encourage participation. We will examine this phenomenon by looking at the affordances and interdependencies that result in our analysis of Twitter campaigns.

Once we understand the processes around user interactions and network mobilization, we analyze the overall information campaign trajectory to get an understanding of how information is diffusing through the network. To do this, we leverage the well-established social science theory of Diffusion of Innovations (DOI). Everett Rogers [1962], who developed the first model of diffusion, defined diffusion of innovation as, "the process by which an innovation is communicated through certain channels over time among the members of a social system". For its adopter, an innovation could be any "idea, practice, or object that is perceived as new by an individual or other unit of adoption" [Rogers, 1962]. The diffusion process consists of four key elements: innovation, the social system which the innovation affects, the communication channels of that social system, and time [Ibid]. Chang [2010] uses the diffusion of innovation theory (DOI) to discuss the adoption of Twitter hashtags. The Rogers and Bass models are presented, and Chang concludes that the theory is appropriate and that the future of hashtag research is twofold using both marketing related variables and a growth model based on the Bass model. Leerapong et al. [2013] uses the Diffusion of Innovation Model to investigate factors that affect online purchase intention via the Facebook OSN. Based on the results of their focus group research, the authors concluded that the determining purchase factors in terms of the adoption of an innovation that the participants were exposed to were relative advantage over the innovation's precursor, trust in the Facebook seller, perceived risk, and compatibility of the innovation with the user's existing values, past experiences and needs.

When we evaluate models using DOI theory, we observe a normal distribution in the adoption cycle. Examining the cumulative frequency of adoption, the model produces an s-curve. S-shaped curves are applied to various applications including predicting population changes, projecting the performance of technologies, and predicting marketing adoption of new technologies. The social network similarly evolves, from an s-shaped pattern of adoption of users and friends to different patterns in path length, diameter, density, and assortativity. Bejan and Lorente [2012] also point out that every successful innovation has this similar trajectory, which is characterized by an initial stage of low acceptance, then another stage when that acceptance begins to spread throughout a population, then at some point that acceptance reaches a critical mass, wherein there is a sharp rise in the acceptance among users, and then, finally, that rate of acceptance reaches a saturation point or ceiling and begins to trail off.

It is important in our work that we provide a method for policymakers to understand if an information campaign has already reached full adoption or critical mass. If information campaigns are caught early enough, policymakers and analysts can monitor the event as it emerges and provide appropriate countermeasures or support. Oliver and Marwell's [1985] critical mass theory show which aspects are important for a critical mass to have successful contract negotiations (e.g., collective action). Oliver and Marwell evaluated the importance of cost, density, and centrality in determining how much individuals are willing to contribute to a cause. This contribution was evaluated in a variety of groups, which varied social ties, interest, and resources in three groups: homogenous groups, heterogeneous social tie groups, and heterogenous ties/interest/resource groups. Overall, while social network density improves collective action (as expected), network centralization remains consistently important (surprising). It is not yet clear if centralization plays a key role in achieving critical mass in a connective action network as one it's tenets is individualized decentralization.

3 Data Collection and Processing

Data for this analysis was collected using the Twitter premium API to collect tweets related to nine COVID-19 topics. The objective was to collect data from January 1 to December 31, 2020 for different misinformation and public discourse hashtags which cover a broad range of topics related to COVID-19 such as lockdowns, face masks, and vaccines. The topics were chosen around highly debated issues that may have some kind of call to action, consistent with connective action campaigns. For each of the three categories, two separate hashtags were analyzed: one representing pro-narratives, and the other representing anti-narratives. For example, hashtags representing anti-narrative campaigns that were collected include: #Nofacemask, #Novaccineforme, and #Lockdownskill. The hashtags representing the corresponding pro-narrative information include: #Wearafacemask, #Vaccinesaveslives, and #Lockdownswork. Additionally, three other hashtags representing conspiracy related topics were analyzed: #Covidscam, #BillGatesVirus, and #Coronascam. The number of resultant tweets for each hashtag is shown in Table 1.

Table 1 - Tweet counts for various COVID-19 hashtags from January 1 to December 31, 2020.

Hashtag	Number of Tweets	Original Tweets	Number of RTs	Number of Mentions
#Lockdownskill	11,630	3,260 (28%)	5,976 (51%)	2,394 (21%)
#Lockdownswork	444	93 (2%)	125 (28%)	226 (51%)
#Nofacemask	740	334 (45%)	276 (37%)	130 (18%)
#Wearafacemask	2,200	1,300 (59%)	760 (35%)	140 (.06%)
#Novaccineforme	12,225	3,827 (31%)	5,816 (48%)	2,582 (21%)
#Vaccinesavelives	305	79 (26%)	193 (63%)	33 (11%)
#Covidscam	13,395	4,165 (31%)	6,482 (48%)	2,748 (21%)
#BillGatesVirus	20,862	2,993 (14%)	10,826 (52%)	7,043 (34%)
#Coronascam	10,592	3,810 (36%)	4,893 (46%)	1,889 (18%)

Our initial observations support a mathematical characterization for connective action campaigns, and then show how affordances can be used to identify the inter-user message strategy. The first approach will drive future work toward developing a predictive model, while the affordance approach will help us to understand if this is organized by multiple users or just a central group of users, at which point we can devise countermeasures or support for the campaign.

4 Methodology

In this section, we discuss the methodological components used in this study to address our objectives of (1) using the DOI model to categorize Twitter users into adoption categories and (2) using s-curves to determine if a campaign has reached its tipping point. Our framework considers two approaches to understanding the diffusion of information in a connective action campaign. In the first approach, we consider *how* OSNs are used for the purpose of social media campaigns. We apply the sociotechnical theories of affordance and interdependence amongst users to understand how individual user participation impacts the rate of adoption into an information campaign. The second process leverages the diffusion of innovations theory to examine the trajectory of the overall campaign as it evolves. Understanding these two processes provides a foundation for predicting when an information campaign reaches critical mass.

4.1 Characterization of User adoption

The interactions between users in a connective action campaign can provide insights to help determine how future actors will react as information propagates through the network. Leonardi distinguished between these types of actions by labeling them as individualized, shared, and collective affordances [Leonardi 2013]. An individual affordance is actualized by one actor acting independently of others; a shared affordance is the same affordance being actualized by many people in similar ways; while a collective affordance involves many people doing different things to accomplish a joint goal (Ibid). Thus, the affordances refer to the way users interact and use digital technology for their purpose of mobilizing additional users. New users will then get exposed to information, and in connective action, will be interdependent on the previous action. Those with interdependent actions are more likely to be conscious of others and their relationships and to adjust their behavior to accommodate others. This type of interdependence between users corresponds to the intensity and behaviors among actors that depend on each other as they accomplish tasks together [Puranam et al. 2012]. These are pooled, sequential, and reciprocal interdependence [Thompson, 1967]. In pooled interdependence each user contributes to the collective action without requiring participation from other users. This is represented through the posting of original tweets, independent of others posting contributions to the event. Sequential interdependence considers the output of a particular user as a requirement for the input to another user. This content is usually unidirectional, and as such, the retweet functionality is representative of sequential interdependence. If the organizational logic follows a pattern of diffusion and not mutual exchanges, the information flow should be rather one-directional than reciprocal [Theocharis, 2017]. Reciprocal interdependence looks at the outputs of users as they become inputs for others, in a bi-directional flow among actors over time. [Vaast, 2017, Bell and Kozlowski 2002]. Users rely on each other, making everyone responsible for accomplishing the goal or task. This can be represented by actors using the "@" mention feature, which allows for a user to directly reply or respond to the actor. In our connective action framework, we assume if group members become increasingly aligned with group norms and expectations, they will behave according to how they believe other people from the same social group will behave and adopt one of these affordance-interdependence actions. Figure 1 summarizes the relationship between these affordances and interdependence. To quantify these relationships, we apply labels to each tweet and graph the cumulative frequency of the campaign tweets over time to identify the affordances and interdependencies for each dataset.

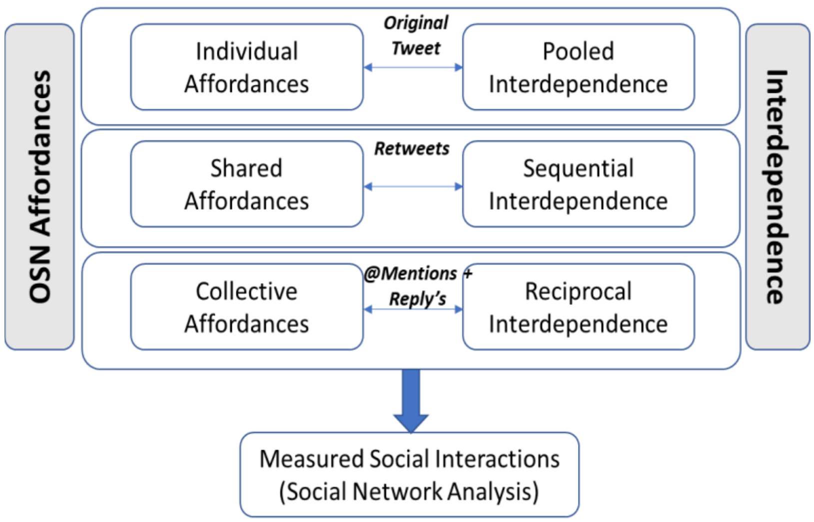


Figure 1 - Relationship between OSN Affordances and Interdependence.

4.2 Characterization of overall campaign cycle

The second approach we use to analyze emerging connective action campaigns is to apply concepts from Diffusion of Innovations (DOI) theory to our analysis. As previously mentioned in the literature review section, DOI theory categorizes users into stages based on where an innovation is in its lifecycle (see Figure 2). When we examine successful information campaigns with a high rate of adoption, we see the cumulative frequency of messaging similarly takes on an s-shaped production function. Analyzing an information campaign from this perspective allows us to see if campaign adoption is accelerating, decelerating, and whether it has reached critical mass (see Figure 3). Applying DOI concepts to our information campaigns, we observe early initiators, amplifiers, and adopters who sustain the campaign until it reaches a steady state of growth or stops growing altogether. We categorize users into these stages and then analyze each stage to understand the user behavior in each stage. To further characterize these campaigns, we look at the rate of change of adoption within the group. The slower the adoption rate, the flatter the "S" curve will be. Whereas, if the adoption rate is fast, the "S" curve will be narrower.

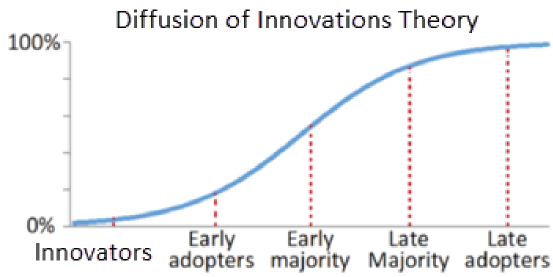


Figure 2 - DOI model and stages for user adoption.

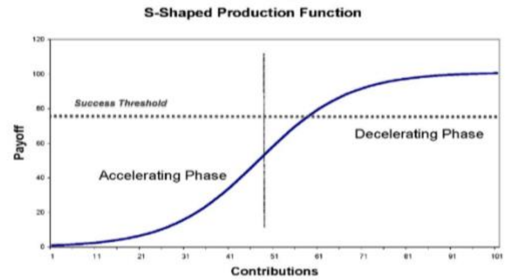


Figure 3 - Model of S-Curve campaign cycle trajectory, with arbitrary success threshold.

In the next section, we discuss the results of our analysis by applying these two methods.

5 Analysis and Results

In this section, we discuss the results of our datasets explored in this work and how they accomplish our objectives of (RQ1) using the proposed affordance-interdependence relationships to show how a campaign unfolds and (RQ2) leveraging the existing social science theory of using s-curves, the Diffusion of Innovations theory, and affordances to provide a mathematical representation of a connective action campaign growth. The first section discusses how we combine the Diffusion of Innovations theory and affordance-interdependence relationship to categorize users into the three stages of an information campaign, i.e., initiators, amplifiers, or sustainers. The second section in our analysis shows how we determined the thresholds for each of the stages we used. Finally, we use differential calculus to identify inflection points on the curves and test our hypotheses of finding where user adoption reaches critical mass.

5.1 User Characterization

In this section, we present our findings from analyzing the affordance-interdependence relationships (RQ1) to show how users can be categorized into adoption stages. We analyzed 9 different datasets from Twitter hashtag networks and plotted the cumulative tweets over time, showing the adoption as it occurs (Figure 4). Examining these 9 connective action campaigns reveals characteristics of the s-shape curve phenomenon. Clearly, there is an initial growth stage, accelerating stage, and then a decelerating stage. However, we notice some campaigns have not fully adopted, and some experience another increase in growth after an initial deceleration. Figure 5 below shows a classic s-curve example of the #billgatesvirus information campaign.

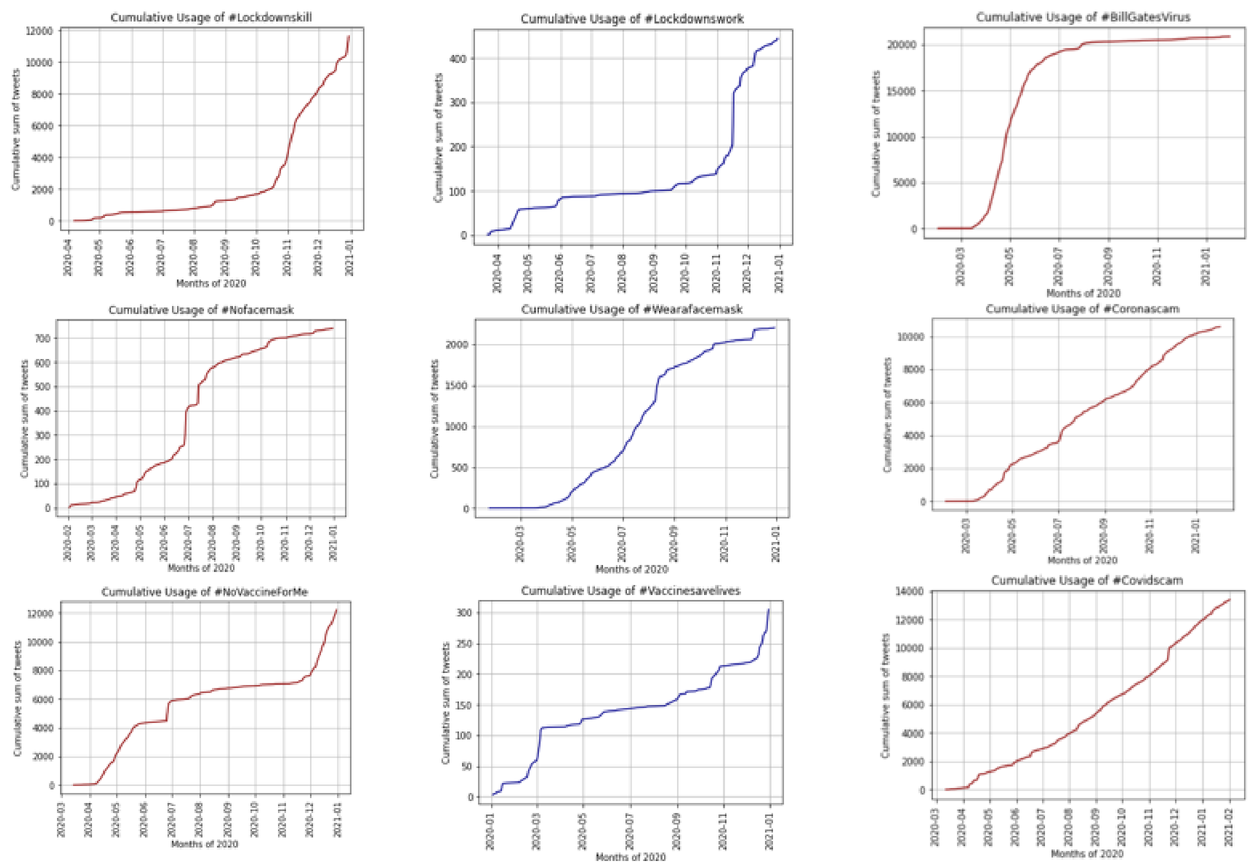


Figure 4 - Cumulative Tweet Frequency for COVID-19 connective action campaigns.

As part of the development of our connective action framework, we need to create a mathematical representation of the event signatures. The previously studied theories of diffusion of innovations and critical mass theory can also be used to characterize these curves into mathematical representations of diffusion for connective action. We initially projected the campaigns onto the five DOI stages and using each percentage from the DOI model, calculated where each stage would occur in time. Next, we calculated the slope at each stage to determine if the slope was similar across campaigns at each of the stages. Using the five stages from the DOI, the slopes were inconsistent across campaigns. See the slope column in Table 2.

Table 2 - Projection of misinformation campaigns onto DOI model stages.

	Innovators Stage 1 - 2.5%			Early Adopters Stage 2 - 13.5%			Early Majority Stage 3 - 34%			Late Majority Stage 4 - 34%			Late Mass Stage 5 - 16%		
	Count of Tweets	Total Time (hours)	Slope	Count of Tweets	Total Time	Slope	Count of Tweets	Total Time	Slope	Count of Tweets	Total Time	Slope	Count of Tweets	Total Time	Slope
LockdownsKill	291	722	0.40	1,861	4,486	0.41	5,815	5,159	1.13	9,769	6,144	1.59	11,630	6,439	1.81
Nofacemask	18	640	0.03	118	2,210	0.05	370	3,541	0.10	622	5,176	0.12	740	7,961	0.09
NoVaccineForl	306	699	0.44	1,956	1,117	1.75	6,112	3,122	1.96	10,268	6,705	1.53	12,224	7,004	1.75
Vaccinesaveliv	8	251	0.03	49	1,202	0.04	153	5,777	0.03	257	8,514	0.03	306	8,690	0.04
Wearafacemas	55	551	0.10	352	1,527	0.23	1,100	3,127	0.35	1,848	4,759	0.39	2,200	6,933	0.32
BillGatesVirus	522	1,233	0.42	3,338	1,636	2.04	10,431	2,082	5.01	17,524	2,922	6.00	20,862	8,734	2.39
AVERAGE			0.24			0.76			1.43			1.61		7,627	1.06

Next, rather than projecting the s-curve onto the DOI stages, we use DOI as our ground truth and apply the concept to our own stages. The early initiation, amplification, and sustainment cycles of these campaigns take on an s-curve shape that is shown in Figure 5. In section 5.3, we describe how we calculate the thresholds for each of the categories. In our conceptual framework, we propose to categorize users into each stage of the campaign for further analysis, such as high influence and bot activity.

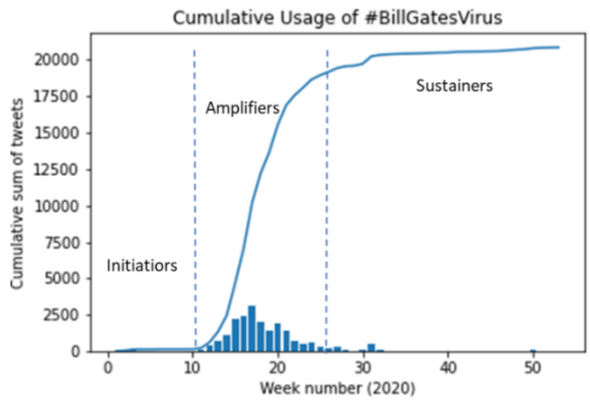


Figure 5 - Overlay of connective action stages onto s-curve campaign.

The next step in our analysis is to examine the affordances of social media and how its use enables new forms of connective action. As previously discussed in section 4.1, the way users interact on social media can determine how future users are mobilized into the network. We examine this affordance relationship by applying labels to each tweet and graphing the cumulative frequency of the campaign tweets over time to identify the affordances and interdependencies for each network. Figure 6 breaks the s-curve into Retweets, Mentions, and Original tweets to examine how information is spread in these information campaigns. As previously mentioned, shared affordances correspond to higher rates of shared social interests that result in sequential interdependence. The interactions that result from this type of interdependence can create higher levels of mobilization than individual-pooled or collective-reciprocal relationships.

Figure 6 shows the #Nofacemask campaign is initially driven by original tweets. About halfway through the campaign, we see that Retweets experience a rapid adoption. By understanding this relationship and knowing that Retweets are part of shared affordances and sequential dependence, we can begin to understand the type of campaign this is and how it is organized. Further, policymakers understanding this, could remove an early node responsible for an early Tweet or Retweets, or add amplification support to a campaign for positive change. Figure 6 shows a sample s-curve campaign with the affordance-interdependence broken out, while Table 1 in section 3 shows the affordance-interdependence relationships between the 9 different connection active campaigns.

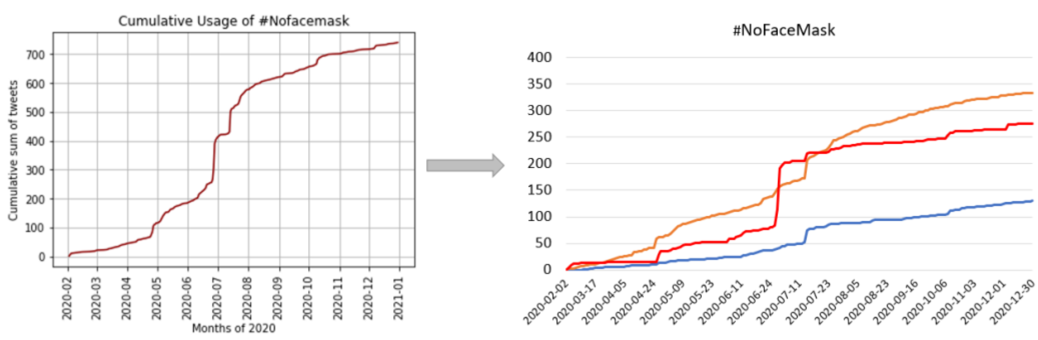


Figure 6 - Breakout of S-Curve into Affordance-Interdependence relationships by Retweets, Mentions, and Original Tweets.

5.2 Characterization of campaign trajectory

In this section, we leverage Diffusion of Innovations theory, and affordances to take a closer look at the overall direction of the information curve as it emerges and apply our methods to help guide our framework towards a mathematical model (RQ2). The s-shaped production function can be seen when we examine information campaigns that have a high rate of adoption and are considered as "successful". We look at the rate of change of adoption within the group in order to characterize these campaigns. A flatter "S" curve is associated with a slower adoption rate. On the other hand, the "S" curve will be narrower, if the adoption rate is fast. These characteristics can be seen when we compare the anti-narrative hashtags campaigns (left graph of Figure 7). When considering the steepness of the curve, we clearly see that some campaigns are slower to adopt than others. It is also evident from the figure that some campaigns have reached critical mass, flattened, and then regained momentum. Of particular interest, when we compared the spread of the pro-narrative campaigns to that of the anti-narrative campaigns, we saw that over the same period the misinformation campaigns were more successful in achieving adoption (right graph of Figure 7).

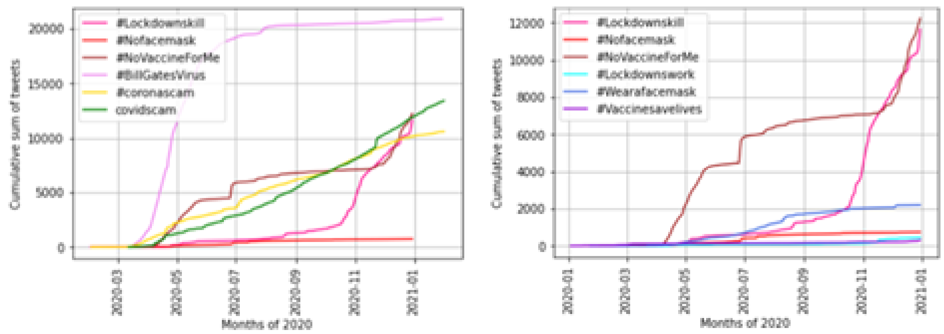


Figure 7 - Contrasting pro vs anti-narrative connective action campaigns.

Our first objective is to apply our analysis from the application of the DOI model to the emerging s-curves. We then apply the second derivative test to identify changes in the slope of the s-curve. The second derivative test is a method in multivariable calculus used to determine if a critical point of a function is a local minimum, maximum or saddle point. This rule is described below:

Suppose $f'(x)=0$ and f'' is continuous over an interval containing x.

If $f''(x)>0$, then f has a local minimum at x.

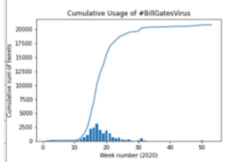
If $f''(x)<0$, then f has a local maximum at x.

If $f''(x)=0$, then the test is inconclusive.

To project our three stages at the right locations we calculate the local minimum, local maximum, and the critical mass or tipping point of the curve. We then overlay our three stages of initiators, amplifiers, and sustainers to each major change in the trajectory of the curve. We propose that this approach will help researchers and policymakers understand if an information campaign is accelerating, decelerating, or has reached critical mass.

Figure 8 highlights the inflection points for each of the information campaigns shown. Column 1 shows the week number, column 2 is the number of users, while column 3 shows the initial *rate of change of tweets* over each week. Column 4 shows the 2nd derivative, or *change in slope,* of the curve for each week. Looking at Figure 8, the boxes from top down, highlighting each row show the change in slope from negative to positive (the first local minimum), from positive to negative (the local maximum or tipping point), and the negative change in slope goes to approximately zero indicating that the slope has reached steady state. The last two campaigns show that neither of these campaigns have reached full adoption and the slope continues to increase.

#BillGatesVirus



Total Users 12434

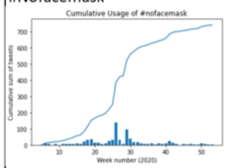
Total Messages 20862

1st inflecti 2nd 306

35	9053	13398
0.23%	59.17%	87.57%

Week	# Users	f'(x) Slope (dT/dt)	f''(x) Change in SMA7
1	2	2.286	0.07
2	10	0.536	-1.75
3	23	3.381	2.85
4	54	0.250	-3.13
5	7	0.029	-0.22
6	10	0.238	0.21
9	1	0.016	-0.22
10	1	0.014	-0.002
11	15	1.039	1.02
12	295	4.774	3.73
13	496	8.033	3.26
14	579	11.245	3.21
15	1685	21.162	9.92
16	1774	21.286	0.12
17	2412	26.471	5.18
18	1689	16.040	-10.43
19	985	10.722	-5.32
20	1184	13.429	2.71
21	1238	9.259	-4.17
22	501	4.461	-4.80
23	437	3.280	-1.18
24	286	3.310	0.03
25	251	1.646	-1.66
26	173	1.253	-0.39
27	186	1.376	0.12
28	128	0.648	-0.73
29	30	0.163	-0.49
30	91	0.638	0.48
31	391	2.369	1.73
32	65	0.406	-1.96
33	34	0.186	-0.22
34	21	0.113	-0.07
35	17	0.061	-0.05
36	9	0.056	-0.01
37	19	0.058	0.00
38	14	0.086	0.03
39	19	0.066	-0.02

#Nofacemask



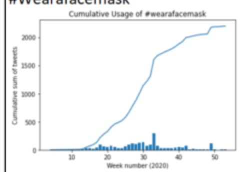
Total Users 573

Total Messages 740

11	358	503
2%	57%	81%

Week	# Users	f'(x) Slope (dT/dt)	f''(x) Change in SMA7
5	1	0.029	0.07
6	10	0.000	-0.03
7	5	0.102	0.10
8	1	0.018	-0.08
9	3	0.079	0.06
10	3	0.014	-0.07
11	5	0.065	0.05
12	3	0.060	-0.005
13	4	0.088	0.03
14	2	0.071	-0.02
15	10	0.095	0.02
16	4	0.045	-0.05
17	5	0.185	0.14
18	20	0.254	0.07
19	34	0.271	0.02
20	11	0.093	-0.18
21	12	0.082	-0.01
22	7	0.045	-0.04
23	10	0.068	0.02
24	21	0.149	0.08
25	21	0.171	0.02
26	54	0.764	0.59
27	112	0.169	-0.59
28	3	0.026	-0.14
29	76	0.473	0.45
30	31	0.181	-0.29
31	17	0.083	-0.10
32	18	0.076	-0.01
33	9	0.048	-0.03
34	6	0.025	-0.02
35	7	0.024	0.00
36	7	0.044	0.02
37	6	0.015	-0.03
38	8	0.034	0.02
39	7	0.022	-0.01
40	8	0.036	0.01
41	10	0.087	0.05

#Wearafacemask



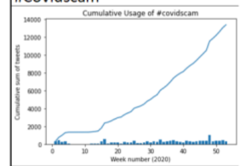
Total Users 1292

Total Messages 2200

52	1229	1272
3%	79%	82%

Week	Users	f'(x) Slope (dT/dt)	f''(x) Change in SMA7
4	2	0.071428571	0.07
12	1	0.05952381	-0.01
13	10	0.087912088	0.03
14	20	0.285714286	0.20
15	19	0.238095238	-0.05
16	25	0.214285714	-0.02
17	30	0.336134454	0.12
18	49	0.714285714	0.38
19	46	0.436090226	-0.28
20	32	0.335714286	-0.10
21	46	0.517006803	0.18
22	38	0.350649351	-0.17
23	18	0.173913043	-0.18
24	16	0.196428571	0.02
25	35	0.331428571	0.14
26	65	0.494505495	0.16
27	76	0.587301587	0.09
28	72	0.540816327	-0.05
29	103	0.620689655	0.08
30	86	0.628571429	0.01
31	60	0.341013825	-0.29
32	63	0.410714286	0.07
33	251	1.29004329	0.88
34	66	0.294117647	-1.00
35	25	0.12244898	-0.17
36	18	0.130952381	0.01
37	20	0.104247104	-0.03
38	22	0.109022556	0.00
39	24	0.142857143	0.03
40	21	0.171428571	0.03
41	15	0.142857143	-0.03
42	18	0.24829932	0.11
43	61	0.03986711	-0.21
44	12	0.051948052	0.01
45	13	0.041269841	-0.01
46	13	0.034161491	-0.01
47	2	0.021276596	-0.01

#Covidscam



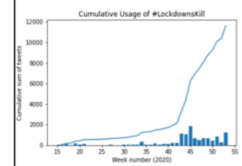
Total Users 7601

Total Messages 13395

278	2110
3%	22%

Week	Users	f'(x) Slope (dT/dt)	f''(x) Change in SMA7
1	75	44.571	0.07
2	203	0.000	-44.57
3	343	11.286	11.29
4	153	10.571	-0.71
5	216	1.114	-9.46
6	56	0.078	-1.04
11	1	0.452	0.37
12	40	0.484	0.031
13	39	0.541	0.06
14	43	3.190	2.65
15	282	5.125	1.93
16	392	0.647	-4.48
17	267	1.214	0.57
18	121	1.444	0.23
19	153	1.129	-0.32
20	156	0.571	-0.56
21	78	1.656	1.08
22	151	1.161	-0.49
23	128	0.917	-0.24
24	145	2.229	1.31
25	327	0.725	-1.50
26	101	0.667	-0.06
27	95	1.051	0.38
28	145	1.606	0.55
29	223	0.981	-0.62
30	171	1.336	0.36
31	202	1.036	-0.30
32	153	2.195	1.16
33	200	1.067	-1.13
34	130	1.204	0.14
35	167	1.488	0.28
36	221	1.683	0.20
37	272	1.105	-0.58
38	278	0.901	-0.20
39	152	0.714	-0.19
40	132	1.247	0.53
41	156	1.017	-0.23

#LockdownsKill



Total Users 6139

Total Messages 11630

163	4661
2%	57%

Week	Users	f'(x) Slope (dT/dt)	f''(x) Change in SMA7
15	2	0.019	0.07
16	14	0.000	-0.02
17	117	1.143	1.14
18	30	0.190	-0.95
19	154	1.414	1.22
20	30	0.343	-1.07
21	80	0.673	0.33
22	10	0.123	-0.550
23	9	0.062	-0.06
24	14	0.101	0.04
25	8	0.051	-0.05
26	9	0.088	0.04
27	16	0.217	0.13
28	15	0.112	-0.10
29	11	0.113	0.00
30	17	0.171	0.06
31	22	0.327	0.16
32	57	0.299	-0.03
33	43	0.225	-0.07
34	264	1.353	1.13
35	29	0.151	-1.20
36	27	0.167	0.02
37	107	0.568	0.40
38	37	0.233	-0.33
39	83	0.359	0.13
40	25	0.332	-0.03
41	134	0.728	0.40
42	122	0.837	0.11
43	788	3.824	2.99
44	590	3.542	-0.28
45	1282	5.825	2.28
46	515	2.146	-3.68
47	306	1.614	-0.53
48	345	1.932	0.32
49	367	1.985	0.05
50	482	1.331	-0.65
51	569	2.345	1.01

Figure 8 - Calculation of inflection points for S-Curve information campaigns, 2nd derivative application.

1 Conclusions and Future Work

The approach taken in this work builds on the diffusion of innovations theory to understand how users adopt information in a connective action campaign. Studying diffusion theory in the context of information diffusion provides valuable insights into the trajectory of an information campaign. Since DOI theory has been applied to various disciplines, a key benefit to this approach is that the s-curves are platform independent. Our experiments on the nine COVID-19 information campaigns have shown that the notion of new innovations transfers nicely to the information environment. Rogers' theory (1962) serves as a comprehensive ground truth for combining our socio-technical framework that measures the affordance-interdependence relationships, and the diffusion elements of the social processes involved in connective action. The contribution of this analysis provides a foundation for mathematical characterization of connective action signatures. The first approach will drive future work toward developing a predictive model, while the affordance approach will help us to understand the organizational components. Our next steps are to parameterize the mathematical equation so that we can more accurately model campaign dynamics. S-curves can take on a logistic sigmoid function, which is the most common activation function used in machine learning algorithms using logistic regression. So, using the sigmoid function may provide a way to calculate the probability of adoption after users are exposed to information. We realize that modeling behavior change may require more than a sigmoid function, but for purposes of developing an initial framework we start here. Future work will also explore the role of bots in the initiation and amplification stages of connective action.

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