

Social Media Virality: Reaching the Tipping Point

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	ABSTRACT
2021 Research Leap/Inovatus Services Ltd. All rights reserved. DOI: 10.18775/jibrm.1849-8558.2015.83.3003 URL: https://doi.org/10.18775/jibrm.1849-8558.2015.83.3003	Social media virality has become a key factor in determining how far to extend social media marketing and digital promotion campaigns. The point at which content transitions to viral spread underpins promotion-level decisions. We employ a logistic equation to identify tipping point decisions for viral content online promotions in given contexts. We consider case studies indicative of viral content on social media following a traditional S-curve when examined in a single domain. Our study contributes to understanding the decision mechanics of reaching a tipping point in a manner that reflects the concerns of digital marketers and online marketing strategies generally. We also see our approach to determining this point as furthering social media research in an area of growing importance and assessing how viral content can be managed.
Keywords: Social media, Virality, Logistic equation, Online marketing	

1. Introduction

Understanding the point at which promotion activities trigger self-propagating reach-out is becoming key to marketing communication decisions. This paper considers the point at which promotion unleashes viral contagion by using a diffusion curve to identify and illustrate the attainment of the social media viral tipping point.

The term ‘tipping point’ refers to the moment at which a small change can alter the balance within a system leading to greater change in a variety of market contexts potentially triggering a rapid increase in a firm’s market share (Dubé et al., 2010; Li et al, 2017; Lin et al. 2015; Miles, 2014; Taran, 2012). Where the ‘cascades’ of information lie to unleash the popularity of content throughout a social network is of growing importance (Zadeh and Sharda, 2022). Testa et al. (2020) point to the relevance of research centered on determinants, activities, and outcomes relating to social media deployment associated with customer growth and relationships. Specifically, in terms of the tipping point for changing social conventions, Centola et al. (2018) found that to be around 25% of the population. The point at which an initial minority opinion quickly turns to that of a majority is around 10% (Xie et al., 2011) whilst Lin et al (2016) point to gender variations in social networking site interactions and impact. Different social settings point to the presence of addictive logic of digital networking (Lambert et al., 2023), ideologies of consumption (Drenten et al., 2023), and displays of consumption as productive activities (Bulmer et al., 2024; Caliandro et al., 2024).

Social media analytics research has not extensively focused on viral promotions management, yet this is a key concern in marketing decision-making (Abbas et al., 2017; Rathore et al., 2017). Our study assesses the tipping point for online viral phenomena by focusing on the domain of promotional content on social media to aid viral marketing decisions. We attempt to localize this point for given online viral phenomena taking into account forces that may promote and hinder its spread. Based on the diffusion of innovations model we propose an equation that assesses the tipping point under two conditions: the first, viral spread under isolation in one domain, and the second, viral spread in multiple interacting domains. The article also models the management of viral content. Examples of such management are a company’s communication officer working to alter some media narrative of a story to its advantage, a government trying to influence its population in one direction rather than another direction, or an investor engaged in spin control to boost its won reputation.

The following section discusses the growing relevance of viral content in the online space. Section 2 discusses viral content. Section 3 addresses the dynamics of the tipping point for such content. We present our model for assessing the tipping point in section 4 followed by three empirical case studies using real-world data intended to test the model in section 5. Section 6 assesses the tipping point in multiple domains. Section 7 models decisions in the management of viral content. Section 8 provides a discussion of our findings and their decision relevance and section 9 concludes the paper.

2. Viral Content

With the rise of digital mediums, organizations have advanced economical, trackable, and scalable alternatives to traditional communication methods (Leitch and Merlot, 2018). These advantages are bolstered by dynamics unique to such mediums, in particular, the ability of their users to consume, create, and disseminate content at will and almost no cost (Lam et al., 2019; Zhang et al. 2019). The combination of these factors allows for promotional content and communication to reach audiences well beyond their initial consideration set, as those who consume the content, share it further within their social networks, creating an information cascade that moves similar to a viral contagion (Hanna et al., 2011; Kalyanam et al., 2007; Kumar and Mirchandani, 2012; Mangold and Faulds, 2009; Marchand et al., 2021; Quesenberry and Coolsen, 2019; Sriram et al., 2015). It is this similarity that has led to this phenomenon being referred to as ‘virality’; and the cascading communication itself being christened as viral content (Gladwell, 2000).

The idea of a tipping point in the context of information spread within society aligns with the theory of critical mass which is part of evolutionary game theory (Zino et al, 2022). The theory suggests that once a dedicated minority crosses a certain threshold of group size (critical mass), the social system passes a tipping point following which the actions of the minority group can result in a cascade effect of behavioral change in society that leads to further acceptance of the minority point of view (Granovetter and Soong, 1983). The theory may also apply to online social networks as it has been shown that the spread of viral content online shows patterns of exponential growth akin to those of a biological virus (Boppolige and Gurtoo, 2017).

Several studies have looked at the tipping point within online social networks. Kawamoto and Hatano (2014) found that the tipping point changed depending on the correlation between spreading rates across generations of their model of an online social network. Additionally, using modeled scenarios Doyle et al. (2016) posited that where the tipping point lies depends on the ‘stickiness’ of the idea or behavior.

Such viral content offers several benefits over traditional marketing and regular paid digital promotion alternatives. The first is the cost-benefit of having users spread the message for free, allowing for exponentially greater exposure than what was paid for. Commonly called ‘earned media’ this user-generated promotion of content is a key performance indicator for most social media campaigns (Ashley and Tuten, 2015). The second benefit that viral content offers over paid content (both in digital and traditional mediums), is that of source credibility (Moldovan et al.; 2022). Studies have consistently found that digital audiences are moving away from official sources and recommendation agents (Ravula et al., 2024) and are increasingly reliant on peers for their information needs (Berthon et al., 2012; Tiago and Verissimo, 2014; Tsai and Men, 2013) especially for high-fit uncertainty products (Yu et al., 2023). This shift in source preference is also accompanied by a shift in the perceived credibility of the source and the message, as studies have found that those peers are now trusted more than official and expert sources (Berthon et al., 2012; Malter et al., 2020; Tiago and Verissimo, 2014; Tsai and Men, 2013; Verma et al., 2023). This has meant that content authored by an official source (such as an advertisement) if received directly from the official course, would be less well-received than if a peer shared it. In cases where content has become viral, it is mostly spread peer-to-peer, meaning that in addition to the cost-benefit, it is imbued with peer credibility even though it was originally authored by an official source.

An outcome of achieving virality of content is that those who share it and forward it to others are themselves highly likely to engage and internalize the promotion. This creates an ever-increasing army of highly involved audience members that can be strategically deployed to support the brand message, the most actively engaged of whom can be retargeted as possible evangelists for the message at hand (Dessart et al., 2015). These benefits make virality a coveted outcome in digital promotions and public communication. The problem is, however, that no consensus exists on what results in virality around which research is lacking (Testa et al., 2019; Winer, 2009). Scholars have offered explanations that range from the relevance, salience, and attractiveness of the content, to its educational, entertainment, and informational values, along with a host of other factors; all of which offer plausible explanations, but no replicable framework as to how to achieve such viral success (Berger and Milkman, 2012; Bruni et al., 2012). As a result, much of the prior research has been summative rather than formative, with no reported study being able to achieve virality in experimental conditions, and no evidence of its achievement on demand. A few studies exist on how to model viral content. Hausken (2019, 2022) models two players seeking to manipulate media conceptions to support each of the two actors engaged in controversial interaction. The analysis illustrates how to handle early versus subsequent evidence of controversies. Hausken (2020) models two competing news organizations striking balances between producing clickbait or fake news on the one hand, and real news on the other hand.

The Covid-19 pandemic involved spread of the SARS-CoV-2 virus, with various implications. Obrenovic et al. (2024) apply bibliometric analysis of various economic consequences during the Covid-19 pandemic crisis to find substantial global collaboration networks and authorships. Nurja and Lahi (2024) find for the Covid-19 pandemic in Albania that young people report decreased psychological well-being and that women report more optimism in 2023. Gerbersgagen and Spath (2023) explore how mortgage

managers experience technology usage during the Covid-19 pandemic. More generally, Obrenovic et al. (2023) use sourcing capability and substitute input to show how a company can sustain its performance during a war-induced crisis.

3. The Viral ‘Tipping Point’ for Promotional Content

It is not clear, in theory or practice, the stage at which specific content becomes viral. It is observed that the information cascade that underlies viral dissemination follows a normal curve, with an exponential increase followed by an exponential decay. This pattern matches the diffusion of innovation models and their associated normal curve characteristics (Johnson, 2012). The view of innovation is that it refers to any idea, product, or service that is perceived as ‘new’ by its target population, and adoption is defined as the population using or consuming the innovation (Rogers, 2003). An innovation is considered successful once a critical mass of people have adopted it and after this point, those who have already adopted it will create enough social inertia for the diffusion to pass through to the rest of the population (Iles et al., 2017; Zhang, 2018).

If this perspective is extended to social media promotional communication, considering it as information that is new for consumers and hence an innovation, with its consumption comparable to the adoption of that innovation; we can map virality onto a diffusion curve. There is support for this as analysis of large online viral events has shown that an S-shaped curve, similar to diffusion, is one of the possible forms that online viral propagation might take (Goel et al., 2015; Johnson, 2012; Langley et al., 2014; Mourdoukoutas and Siomkos, 2009). Consequently, if the spread of social media information mimics the diffusion of an innovation, it would need to reach a critical mass audience before it achieves virality or a ‘tipping point’ after which it would enter a stage of automatic information cascade (Xiong et al., 2016).

The identification and mapping of such a tipping point would serve digital communication efforts immensely as it could help provide clear goalposts, key performance indicators, and a running diagnostic to ensure that the communication campaign is headed toward the tipping point for viral contagion (De Bruyn and Lilien, 2008; Shakarian et al., 2013). It can also help predict the size of the total viral load (number of people reached through virality) before a campaign is over, resulting in informed decision-making on paid boosts to keep the campaign running.

Identification of the tipping point allows for further investigation into the factors that modify its threshold and even accelerate its onset (Kawamoto and Hatano, 2014; Singh et al., 2020). Some examples of such factors investigated or recommended include the effects of semantic trends on the tipping point (Hillerbrand, 2016), deployment of long-tail marketing strategies (Vukanovic, 2011), the impact of local networks and consumer characteristics (Moldovan et al., 2019; Yoganarasimhan, 2012), community organization (Yildirim et al., 2020) and the effects of manipulating diffusion characteristics of the communication (Mourdoukoutas and Siomkos, 2009).

Rogers (2003), in his diffusion of innovations model, places the tipping point, or the moment of entering ‘hypergrowth’, at the point where 16% of the target population has received the message. This percentage will be compared with alternative percentages in the empirical case studies below. It is at this point that the message will either become viral or lose momentum and experience exponential decay in audience growth. Figure 1 illustrates this phenomenon.

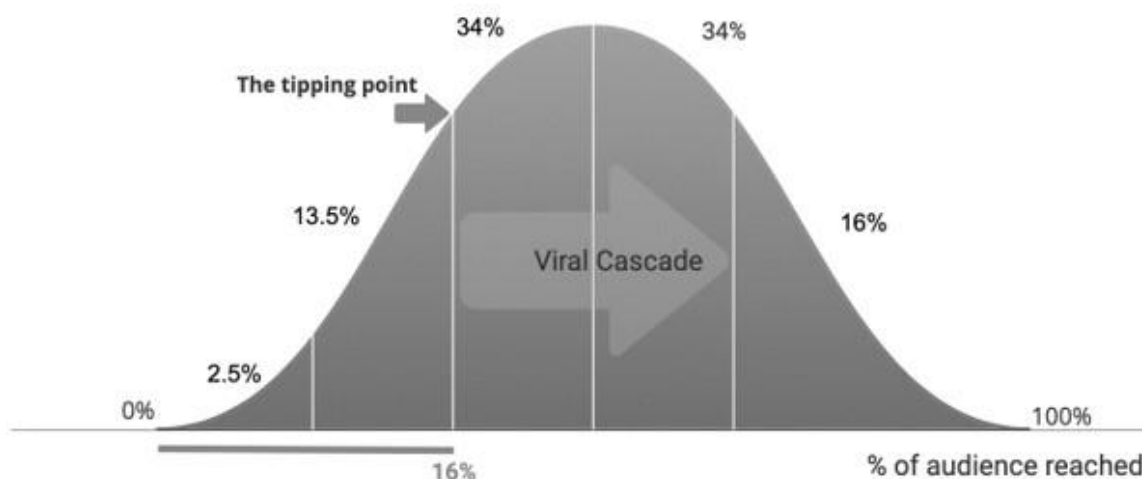


Figure 1: The tipping point for viral information

Extant literature on diffusion models is primarily based on the idea that diffusion constitutes a binary state change and individuals are classified as adopters or non-adopters (Landsman and Givon, 2010). While some models do account for intermediate states such as awareness and non-awareness, these states function at the aggregate level rather than at the individual (Mahajan et al., 1984). However, such models frame the adoption process as a slow, gradual change which is unsuited for the rapid time scale of online viral media where the time difference between “awareness” and “adoption” (in this case viewing the content) is much shorter than it would be for adopting a product.

Under the diffusion framework, up until reaching the tipping point, the message is diffusing through two specific behavioral categories of people, those who are impulse adopters (innovators), and those who curate the decision to adopt for others (early adopters). It is the latter, the early adopters, who serve as influencers in modern social media parlance; a set of more engaged users who are relied upon by the larger majority to parse through new information and assist in their decision to consume (adopt) it or not. This implies that influencers are crucial to ensuring that a message reaches the tipping point, making ‘influencer marketing’ an imperative for modern social media campaigns. The following section will consider locating the tipping point using a logistic equation in a single domain.

4. Tipping Point via One Domain

Consider a domain k , $k = 1, \dots, N$, in which viral content may spread, where N is the number of domains. A domain may be the internet as such, or subsections of the internet demarcated geographically, by user characteristics, by topic (e.g., news on climate change), or in any way on which some demarcation can be established. We define the amount of viral content at time t in domain k as x_k , $0 \leq x_k \leq x_{kmax}$, where x_{kmax} is the maximum possible amount of viral content in domain k . Viral content, if it gets off the ground, may follow an S-shaped curve through time. Initially, the increase may be slow and convex. Subsequently, the increase may be more rapid, with a gradual transition to a concave increase. Finally, the increase may slow down causing viral content to approach a horizontal asymptote x_{kmax} . The logistic equation (Lotka, 1924; Verhulst, 1845) is usually expressed as

$$\frac{\partial x_k}{\partial t} = r_k x_k \left(1 - \frac{x_k}{x_{kmax}}\right) \quad (1)$$

$$\Rightarrow x_k = \frac{x_{kmax} x_{k0} e^{r_k t}}{x_{kmax} + x_{k0} (e^{r_k t} - 1)}, x_k = x_{kmax}$$

where ∂ means differentiation, t is time, r_k is the growth rate which expresses how quickly viral content spreads, and x_{kmax} is the carrying capacity. Equation (1) states that viral content x_k in domain k changes logistically from x_{k0} , $x_{k0} \geq 0$, at time $t = 0$ towards $x_k = x_{kmax}$ as time t approaches infinity.

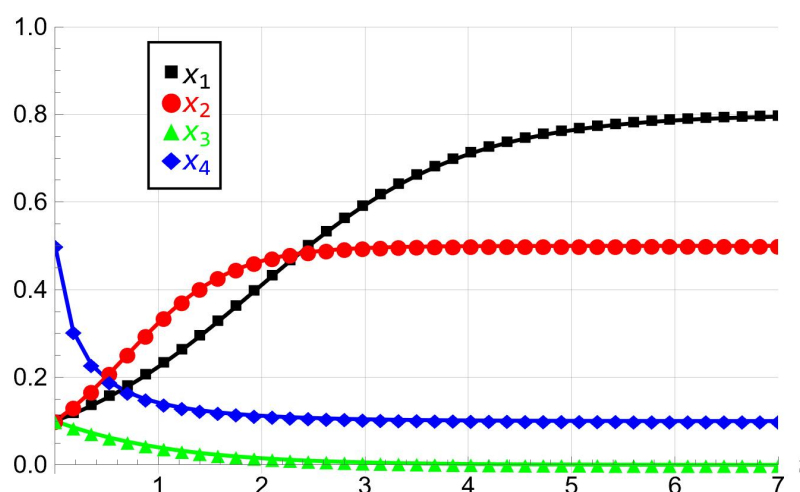


Figure 2: The evolution of viral content x_k , $k = 1, 2, 3, 4$, and in four domains, $x_1(t = 0) = x_2(t = 0) = x_3(t = 0) = 0.1$, $x_4(t = 0) = 0.5$, $r_1 = r_4 = a_k = 1$, $x_{1max} = x_{3max} = 0.8$, $r_2 = 2$, $x_{2max} = 0.5$, $r_3 = -1$, $x_{4max} = 0.1$

Domains opposing viral content, due to cultural, legal, economic, or technological, reasons, have a low carrying capacity x_{kmax} , which may equal zero e.g., if viral content is illegal or technologically unavailable. In contrast, domains available for, welcoming, or encouraging viral content have a high carrying capacity x_{kmax} . Also, domains with low inertia, high willingness to explore or adapt to the presence of viral content, and competence and resources to implement changes facilitating viral content, have high growth rate r_k . Domains without these characteristics have low growth rate r_k .

Figure 2 illustrates the logistic evolution of viral content x_k , $k = 1, 2, 3, 4$, in four domains by plotting as functions of time t , assuming initial viral contents $x_1 = x_2 = x_3 = 0.1$ and $x_4 = 0.5$ at time $t = 0$. Domain 1 is assumed to facilitate the spread of viral content at intermediate speed, expressed with an intermediate growth rate $r_1 = 1$, but to enable substantial eventual spread expressed with high carrying capacity $x_{1max} = 0.8$. In contrast, domain 2 is assumed to facilitate the spread of viral content at high speed, expressed with a high growth rate $r_2 = 2$, but to enable intermediate eventual spread expressed with intermediate carrying capacity $x_{2max} = 0.5$. The point at which a shift or tipping occurs, tentatively defined here as a 25% spread (marked with a horizontal dashed line), is reached earlier for domain 2 than for domain 1. The viral contents x_3 and x_4 are discussed in section 7.

5. Case Illustrations

This section examines the applicability of the model to real-world data. We consider three case studies based on data retrieved from the CMU Viral Video Dataset to model the spread of viral content on the YouTube platform. The dataset contains data for 446 viral videos on the YouTube platform from 2010 to 2012. The data includes video metadata as well as information on the number of views, likes, dislikes, and comments. The following example applies the tipping point model to the “PSY - GANGNAM STYLE (M/V)” video present within the dataset. Gangnam Style is a music video uploaded to YouTube by the creator PSY. On 15/07/2012 it achieved the maximum recorded views (1206879985) at the time of data capture which is the highest in the dataset. Gangnam Style is notable for its rapid growth and global interest. It became the most popular video on YouTube for 5 years running ((Jiang et al., 2014; Jung and Li, 2014; Savage, 2017)).

For this example, we consider YouTube to be the domain k , wherein the viral content (Gangnam Style) at time t is denoted by x_k . As there is no limit to the number of views a video can get, the maximum possible amount of viral content x_{kmax} can be infinite. Therefore, for this example, we have set x_{kmax} to the highest number of views recorded on the YouTube platform as of September 2020.

For calculating the viral content x_k on day 5 ($t=5$), we can use the first recorded observation (Day 3) as $x_{k0}=1448640$. Growth rate r_k has been calculated using the following formula:

$$r = (x_n/x_0)^{1/n} - 1 \quad (2)$$

where x_n and x_0 are the first and last recorded values for the video in the dataset respectively and n is the number of days from the first observation to the last, giving us the value of $r_k=0.0726$. The parameter x_{kmax} is set as the maximum number of recorded views (6902693250). By inserting these values into equation (1), we obtain the value of x_k at day 5, i.e.

$$x_k = \frac{6902693250 \times 1448640 e^{0.726 \times 5}}{6902693250 + 1448640 (e^{0.726 \times 5} - 1)} = 2056076.1 \quad (3)$$

Repeating this process for the remaining observations we can plot the logistic evolution of the viral content x_k as a function of time t , see Figure 3.

Using another example from the CMU viral video dataset we can observe that the pattern of virality applies to data sampled over a longer time period (515 days compared to 184 for Gangnam Style). Using the same methodology used in the Gangnam Style case study, we applied the model to the music video “The Wanted - Glad You Came”, uploaded by the “thewantedVEVO” channel on 11/08/2011. At the time of data capture, the video had received 64522445 views. Using the equation from case study 1, the growth rate was calculated to be $r_k=0.0726$. Inserting these values into equation (1), and using the first recorded observation from day 20, we can calculate x_k for $t=26$, i.e.

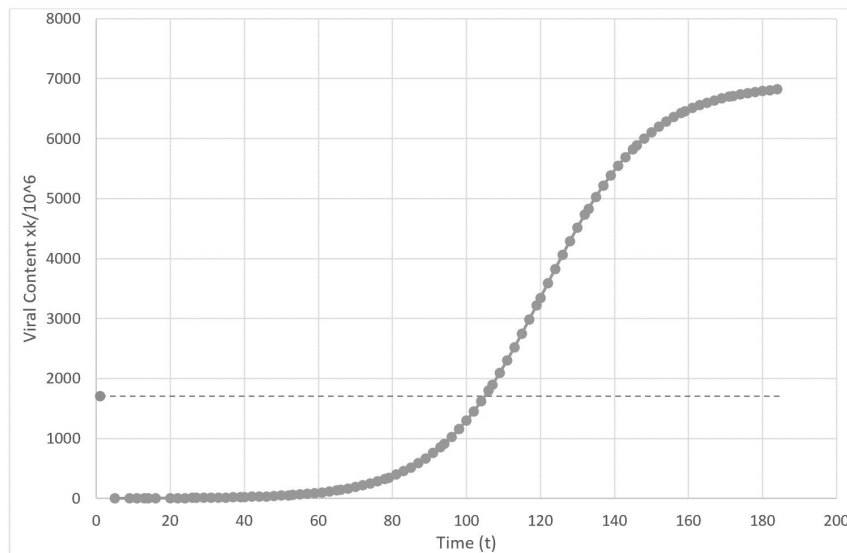


Figure 3: Evolution of Viral Content for “PSY - GANGNAM STYLE (M/V)” on YouTube. Note. The dashed line represents 25% viral spread

$$x_k = \frac{6902693250 \times 77265 e^{0.0726 \times 26}}{6902693250 + 77265 (e^{0.0726 \times 26} - 1)} = 477492.5 \quad (4)$$

Repeating this process for the remaining values, we can see how viral content x_k evolves as a function of time t for “The Wanted - Glad You Came,” see Figure 4.

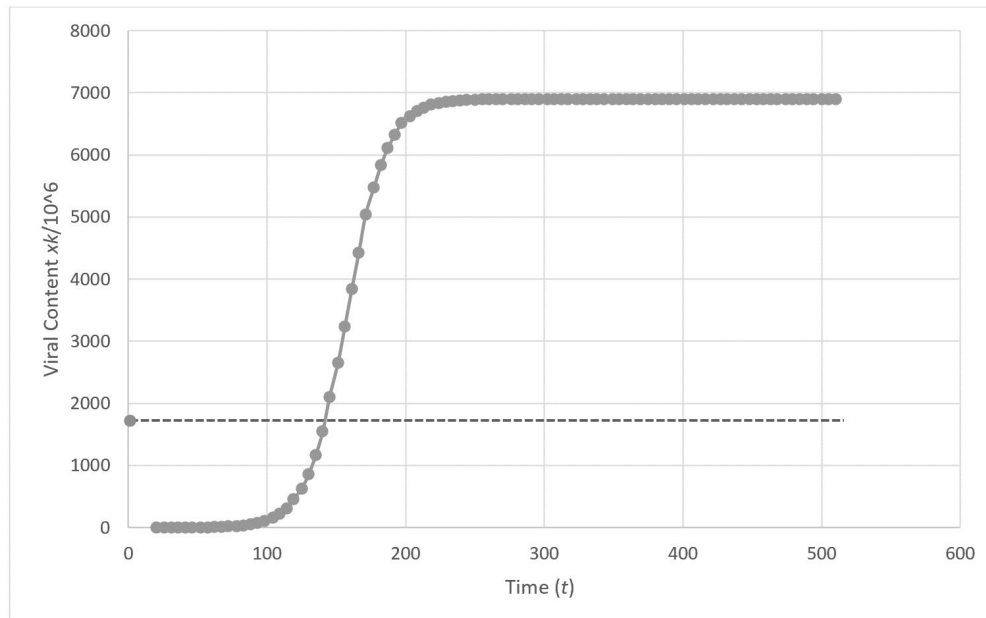


Figure 4: Evolution of Viral Content for “The Wanted - Glad You Came” on YouTube. Note. The dashed line represents 25% viral spread

Here we compare the examples from case studies 1, 2, and a third example (Rebecca Black-Friday) to assess how viral content of a similar nature but from divergent cultures can spread within a single domain. Similar to case studies 1 and 2, we determined the growth rate for “Rebecca Black-Friday”, uploaded by the channel “Rebecca” on 16/09/2011 to be $r_k = 0.0813$ and calculated x_k values for each recorded observation, plotting them as a function of time t , see Figure 5.

Comparing the three case studies we find that the spread of Gangnam Style is slower than the other two songs by English-speaking artists, although out of the three songs Gangnam Style has a significantly higher number of views. This may speak to inherent cultural barriers like language and specific references within the song that individuals outside Korea may not be aware of (Meza and Park, 2015).

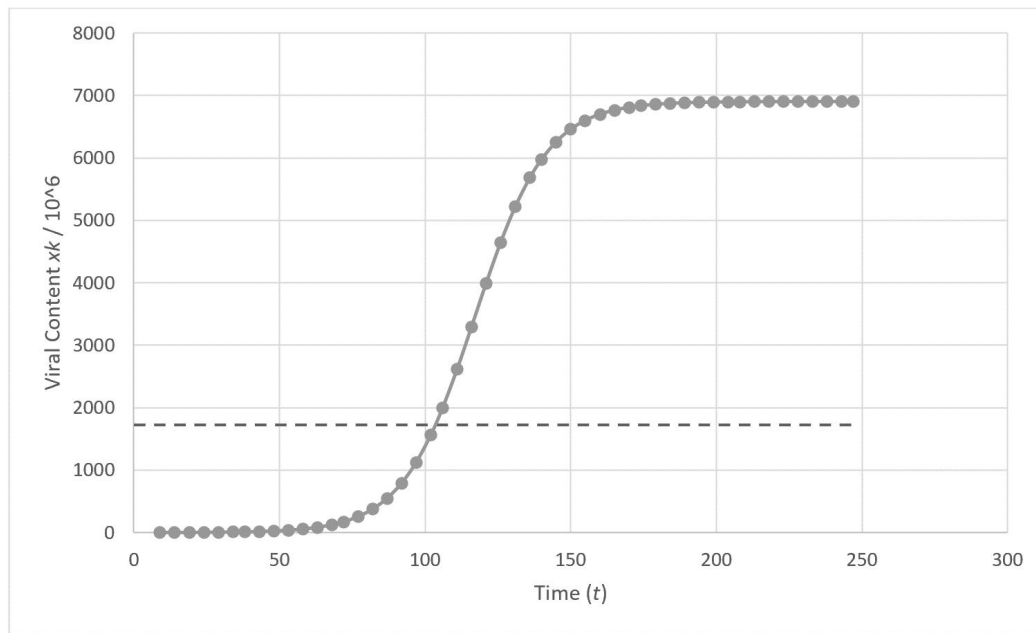


Figure 5: Evolution of Viral Content for “Rebecca Black-Friday” on YouTube. Note. The dashed line represents 25% viral spread

6. Locating the Tipping Point in Multiple Domains

Thus far we have looked at viral spread in a single domain but the spread of viral content often does not occur in a vacuum in one given domain. Technology, economics, culture, and interest of providers, users, and regulators impact the role of viral content, which may compete with other phenomena. Equation (1) and Figure 2 assume no interaction between the N domains. Thus, with a positive growth rate r_k viral content x_k increases and cannot decrease. Given that viral content x_k may increase in several domains, or it may increase in one domain and decrease in another domain, etc. Equation (1) generalizes to

$$\frac{\partial x_k}{\partial t} = r_k x_k \left(1 - \frac{\sum_{h=1}^N \alpha_{hk} x_h}{x_{kmax}} \right) \quad (5)$$

where α_{hk} is the impact of domain h on domain k . Positive α_{hk} 's means competitive or harmful impact. That is, increased viral content x_h in domain h decreases the viral content x_k in domain k . In contrast, and perhaps more likely, negative α_{hk} 's means beneficial impact, i.e. that increased viral content x_h in domain h increases the viral content x_k in domain k , so that domains h and k reinforce each other's adoption. The self-interacting terms are commonly set to $\alpha_{hh} = 1$, $h = 1, \dots, N$. Bomze (1983, 1995) classifies the dynamics of equation (5) for all sign combinations of α_{hk} .

7. How to Manage Media Virality?

This section models how marketing managers may actively manage media virality. One approach is to assume that a manager can somehow alter the growth rate r_k for how quickly viral content x_k spreads in domain k , $k = 1, 2$, or alter the carrying capacity x_{kmax} for how extensive the virality may become. A transition from curve x_1 to curve x_2 in Figure 2 exemplifies an increased growth rate from $r_1 = 1$ to $r_2 = 2$, and a decreased carrying capacity from $x_{1max} = 0.8$ to $x_{2max} = 0.5$. The opposite transition from curve x_2 to curve x_1 exemplifies the opposite. Curve x_3 in Figure 2 assumes a negative growth rate $r_3 = -1$ and carrying capacity $x_{3max} = 0.8$, which causes a decrease from $x_3(t = 0) = 0.1$ towards $\lim_{t \rightarrow \infty} x_3 = 0$. Curve x_4 in Figure 2 assumes a positive growth rate $r_4 = 1$ and carrying capacity $x_{4max} = 0.1$, which causes a decrease from $x_4(t = 0) = 0.5$ towards $\lim_{t \rightarrow \infty} x_4 = 0.1$.

An alternative to the approach in Section 4 and Figure 2 is to assume that a manager cannot alter the growth rate r_k and the carrying capacity x_{kmax} . This section assumes that a manager in domain k at time t exerts intervention effort m_k , $m_k \in \mathbb{R}$, at unit cost a_k , $a_k \geq 0$, to manage media virality x_k . Constraining virality occurs when $m_k > 0$, no impact occurs when $m_k = 0$, and increasing virality occurs when $m_k < 0$. Inserting $-a_k m_k$ on the right-hand side of equation (1) gives

$$\begin{aligned} \frac{\partial x_k}{\partial t} &= r_k x_k \left(1 - \frac{x_k}{x_{kmax}}\right) - a_k m_k \\ \Rightarrow x_k &= \frac{x_{kmax}}{2} - \frac{\sqrt{x_{kmax}} \sqrt{4a_k m_k - r_k x_{kmax}}}{2\sqrt{r_k}} \tan(A), \\ A &\equiv \frac{t\sqrt{r_k} \sqrt{4a_k m_k - r_k x_{kmax}}}{2\sqrt{x_{kmax}}} + \text{ArcTan} \left(\frac{\sqrt{r_k} (x_{kmax} - 2x_{k0})}{\sqrt{4a_k m_k - r_k x_{kmax}}} \right) \end{aligned} \quad (6)$$

which is illustrated in Figure 6.

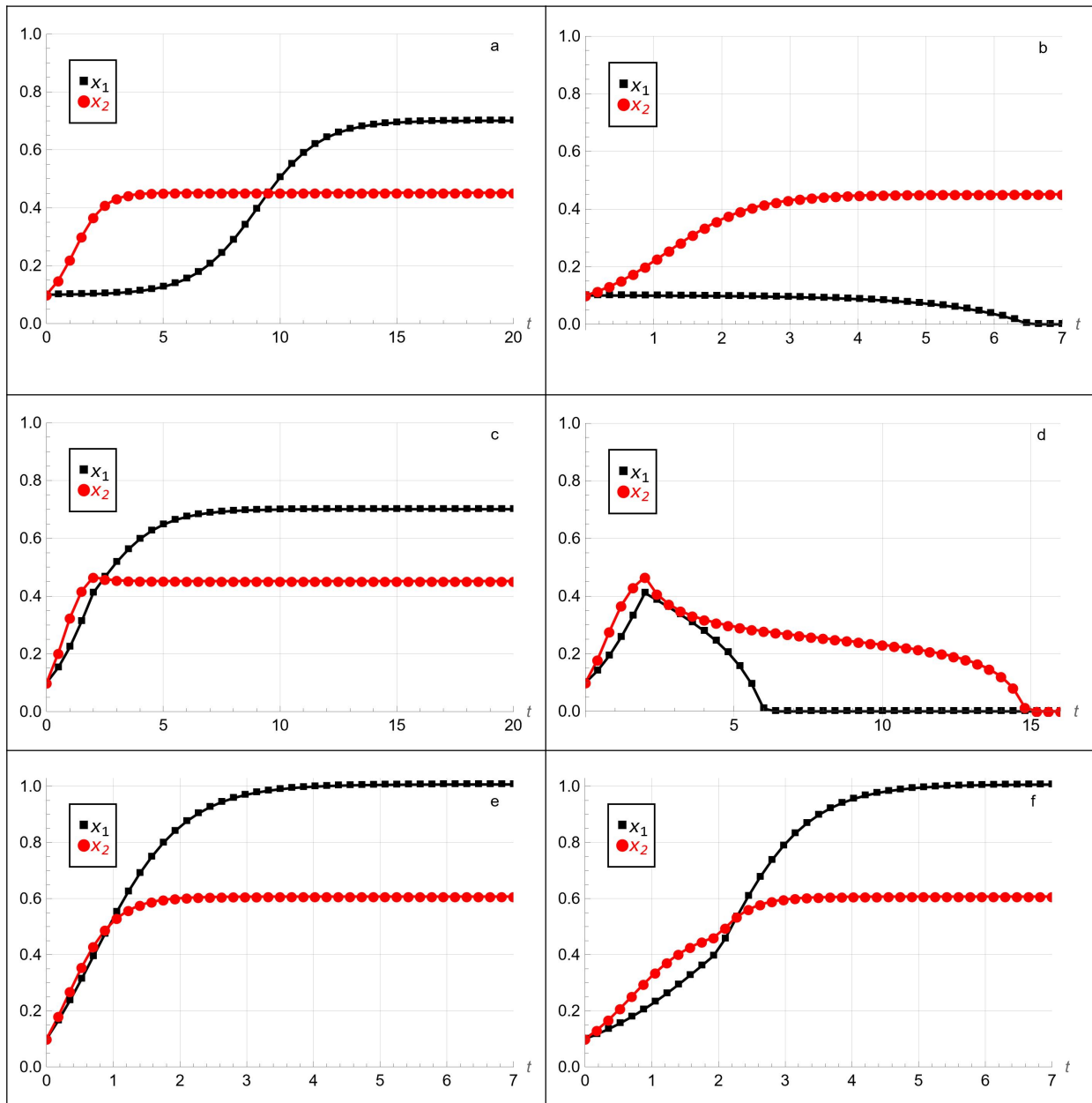


Figure 6: The evolution of viral content x_k in domain k , $k = 1, 2$, when media virality from time $t = t_m$ is managed by exerting effort m_k at unit cost a_k , $x_1(t = 0) = x_2(t = 0) = 0.1$, $r_1 = a_k = 1$, $x_{1max} = 0.8$, $r_2 = 2$, $x_{2max} = 0.5$. Panel a: $m_k = 0.087$ when $t \geq 0$.

Panel b: $m_k = 0.088$ when $t \geq 0$. Panel c: $m_k = 0.087$ when $t \geq 2$. Panel d: $m_k = 0.087 \times 3$ when $t \geq 2$. Panel e: $m_k = -0.087 \times 3$ when $t \geq 0$. Panel f: $m_k = -0.087 \times 3$ when $t \geq 2$

All the six panels in Figure 6 make the same assumptions as for domains $k = 1$ and $k = 2$ in Figure 2, i.e. initial values $x_1(t = 0) = x_2(t = 0) = 0.1$, $r_1 = 1$, $x_{1\max} = 0.8$, $r_2 = 2$, $x_{2\max} = 0.5$. Additionally, the unit effort cost $a_k = 1$ is assumed. The manager's effort m_k is assumed operational when $t \geq t_m \geq 0$, and not operational when $0 \leq t < t_m \geq 0$.

Figure 6a assumes the effort $m_k = 0.087$ when $t \geq 0$. That causes the viral content x_1 to increase more slowly than in Figure 2 and approach a lower level $\lim_{t \rightarrow \infty} x_1 = 0.70$. All limit values are determined numerically. The viral content x_2 also approaches a lower level $\lim_{t \rightarrow \infty} x_2 = 0.45$.

Figure 6b assumes the slightly higher effort $m_k = 0.088$ when $t \geq 0$. That causes the viral content x_1 to decrease to $x_1 = 0$ when $t \geq 6.51$.

Figure 6c assumes the effort $m_k = 0.087$ when $t \geq 2$, and no effort $m_k = 0$ when $0 \leq t < 2$. That causes the viral contents x_1 and x_2 to increase more slowly than in Figure 6a, and approach $\lim_{t \rightarrow \infty} x_1 = 0.70$ and $\lim_{t \rightarrow \infty} x_2 = 0.45$.

Figure 6d assumes three times as high effort $m_k = 0.087 \times 3$ as in Figure 6c when $t \geq 2$, and no effort $m_k = 0$ when $0 \leq t < 2$. That causes the viral contents x_1 and x_2 to decrease and be contained, reaching $x_1 = 0$ when $t \geq 6.04$ and $x_2 = 0$ when $t \geq 14.85$.

Figure 6e assumes that the manager seeks to increase the viral content by exerting negative effort $m_k = -0.087 \times 3$ when $t \geq 0$. That causes the viral contents x_1 and x_2 to increase more quickly than in Figure 2, and approach $\lim_{t \rightarrow \infty} x_1 = 1.01$ and $\lim_{t \rightarrow \infty} x_2 = 0.61$.

Figure 6f assumes that the manager seeks to increase the viral content by exerting negative effort $m_k = -0.087 \times 3$ when $t \geq 2$, and no effort $m_k = 0$ when $0 \leq t < 2$. That causes the viral contents x_1 and x_2 to increase as in Figure 2 when $0 \leq t < 2$, and thereafter to increase more quickly, and approach $\lim_{t \rightarrow \infty} x_1 = 1.01$ and $\lim_{t \rightarrow \infty} x_2 = 0.61$.

8. Discussion

We have argued that the growth rate r_k of viral is contingent upon the carrying capacity $x_{k\max}$. In practical terms, this means that the spread of viral content is limited by the platform used. Online platforms with fewer visitors, content, or infrastructure to support a large number of users would naturally have a lower carrying capacity, whereas platforms with a greater number of users, content and infrastructure to provide uninterrupted service to a large number of users, would have a high carrying capacity.

While what content appeals to a large audience and thus viral may exhibit only partial determinism, platforms that host content can create conditions where a piece of content can reach virality. This starts with an examination of factors that could increase the growth rate r_k and the carrying capacity $x_{k\max}$ of domains (platforms). The first of which, ease of access to a platform and its user-friendliness in terms of its navigability, contributes to user retention (Braun, 2013) which leads to larger user bases, in turn creating greater carrying capacity for the domain. Secondly, we have uninterrupted service. Constant uptime is essential for users to access the platform at all hours (Zhou and Zhang, 2009). User loyalty is negatively affected by a lack of instant availability and gratification, thereby consistent access is key to retaining users and preventing them from migrating to other platforms. Thirdly, availability on more than one technological medium. A platform is more likely to reach a greater number of users, and hence have greater carrying capacity, when it offers support for more than one technological medium e.g., computers, android, iOS, etc. Fourth, availability in multiple territories has a great impact on both growth and carrying capacity. To maximize the number of users that can be reached, online content platforms aim to be available in a large number of countries. Even though most online services can be accessed by default from anywhere in the world unless explicitly geo-fenced, making a platform available across territories is a resource-intensive task involving compliance with local customs and regulations. Such compliance increases the acceptability and hence carrying capacity of the platform at hand. Fifth, local creators can be leveraged to great effect. Greater homogeneity of content with the cultures, experiences, and language of consumers also results in larger, more involved user bases, and hence greater growth rate of such localized content. For example, hosting local creators with large followings is essential for services looking to expand into non-English speaking markets, and localized versions (commentary, translations, re-enactment, etc.) of international viral content accelerates its growth in such conditions (Mohan and Punathambekar, 2019). Lastly, we have to balance free versus paid access to content: Gatekeeping content behind paywalls limits its attractiveness to consumers and thus limits its potential for virality (Kammer

et al., 2015). This reduces the overall carrying capacity of the platform (as paid sections become unavailable by default, reducing the effective user base to a subset of the original, i.e., only those motivated enough to be willing to pay. Placing a cost on the consumption and sharing of content also makes it a higher involvement decision as compared to free alternatives, which mandates greater discretion, scrutiny, and editorial control by the users, negatively affecting the average growth rate of content overall. Platforms can increase their carrying capacity and growth rate by ensuring greater volumes of freely consumable and sharable content and looking at alternate forms of revenue generation (as opposed to paywalls for content).

We consider also factors that impede growth rate and/or carrying capacity for online viral content, starting with maintenance. Server upkeep, especially video hosting demands significant upfront investment into server infrastructure as well as ongoing maintenance for uninterrupted service. Scaling the carrying capacity upwards, therefore, requires a significant logistic and financial undertaking. Next government censorship is a significant roadblock to potential growth. Complying with government regulations with regard to limits on speech, especially with differing regulations across territories, is an intensive and involved process. This process becomes exceedingly difficult as the user base grows and the amount of content uploaded increases (Chen and Berger, 2013), placing limitations on platform growth and localization, thereby limiting both the growth rate and the platform's carrying capacity as a result. Another limiting factor is age-restricted content: The universality of content further mediates its potential virality. Content limited to a certain segment of the population is unlikely to have the same potential of virality as content available to all ages. Content restricted to sub-audiences thereby already receives a reduced version of the platform's carrying capacity. Finally, many legal issues plague online content resulting in protracted and expensive legal battles. These include issues of copyright, content monetization, content moderation, as well as civil and social impact among others. The spread of viral content is not limited to one platform. The ease of spread of viral content on one platform may affect its spread on another platform. Given the limited availability of comparable cross-platform metrics for viral content, this area of study may benefit from more standardized data collection.

Identifying the tipping point for social media viral content has significant implications for the academic as well as applied use of social media across a variety of topics and industries. The determination of a tipping point for virality on social media presents an opportunity to create clearly defined performance indicators for social media content while also opening new avenues of investigation into the mechanisms underlying this threshold (Chung et al., 2022). Knowing not only the exact point of inflection but also the carrying capacity and growth rate of each domain, as well as the factors that affect them; allows for both strategizing and diagnosing progress towards virality. This knowledge could be used to generate new frameworks and provide support across a multitude of fields in a manner not overly technical (Biswas, 2014). Such developments would provide both explanatory and predictive power to academic and applied endeavors that utilize or investigate the role of social media across a range of areas such as uptake of health products (Vaghefi et al., 2024), civic behavioral changes (Rosario et al.; 2022), entertainment consumer engagement (Gupta et al., 2024), e-governance (strategic goals for policy initiatives, KPIs for e-participation, ICT adoption), e-commerce (digital marketing metrics, influencer based-WOM efficacy, digital product development), development sector (indicators and predictors of social transformation, MandE metrics, feasibility analysis), and finance (fintech adoption, assessment and of digital currencies and financial products) (Njilla et al., 2016).

Although the YouTube dataset utilized in this article is rich, it is also limited, because YouTube is only one particular type of social media. Future research should extend to other datasets. One strength of this article is to illustrate the existence of a social media virality tipping point. Future research should delve into the factors that influence, affect, and impact when something on social media becomes viral.

9. Conclusion

This study advances an alternative approach to determining the tipping point for viral content in social media communication. We have applied a logistic equation to three empirical case studies retrieved from the CMU Viral Video Dataset. We demonstrate possible applications of the model to virality data in determining the positioning of the tipping point where content transitions from modest to viral spread which has found little reporting in the literature (Moe et al. 2018; Singh et al., 2020). Our results show that social media viral content follows a traditional S-curve when examined in a single domain. With the proliferation of the internet and social media, a better understanding of the mechanisms underlying tipping points allows for the artificial creation of viral spread which is of importance for social media researchers, digital marketers, and online marketing strategies (King et al., 2014; Malthouse and Shankar, 2009; Reichstein and Brusch, 2019). There are significant implications for businesses and companies especially those with limited financial resources in finding and manipulating the factors that drive viral content for marketing and communication. While this investigation enhances our understanding of factors that influence viral marketing, it points also to the value of future research that examines the effects of macro-level variables like social media network dynamics as well individual factors such as affective response to viral content on tipping point variability.

References

- Abbas, A., Simon, J., and Smith, C. (2017) Introduction to the Special Issue on Decision Analysis and Social Media. *Decision Analysis* 14(4), 227-228. [CrossRef](#)
- Ashley, C., and Tuten, T. (2015). Creative Strategies in Social Media Marketing: An Exploratory Study of Branded Social Content and Consumer Engagement. *Psychology and Marketing*, 32(1), 15–27.
- Berger, J., and Milkman, K. L. (2012). What Makes Online Content Viral? *Journal of Marketing Research*, 49(2), 192–205.
- Berthon, P. R., Pitt, L. F., Plangger, K., and Shapiro, D. (2012). Marketing meets Web 2.0, social media, and creative consumers: Implications for international marketing strategy. *Business Horizons*, 55(3), 261–271.
- Biswas, D. (2014), Editorial: Making Behavioral Research More Practically Relevant, *Journal of Consumer Marketing*, Vol. 31 No. 5.
- Bomze, I. M. (1983). Lotka-Volterra equation and replicator dynamics: A two-dimensional classification. *Biological Cybernetics*, 48(3), 201–211. [CrossRef](#)
- Bomze, I. M. (1995). Lotka-Volterra equation and replicator dynamics: New issues in classification. *Biological Cybernetics*, 72(5), 447–453.
- Boppolige, A. A., and Gurtoo, A. (2017). Growth of a viral phenomenon: Development and testing of a new methodological framework. *Australasian Marketing Journal*, 25(1), 57–66.
- Braun, M. T. (2013). Obstacles to social networking website use among older adults. *Computers in Human Behavior*, 29(3), 673–680.
- Bruni, L., Francalanci, C., and Giacomazzi, P. (2012). The Role of Multimedia Content in Determining the Virality of Social Media Information. *Information*, 3(3), 278–289.
- Bulmer, S., Palakshappa, N., Dodds, S. and Harper, S. (2024). Sustainability, brand authenticity and Instagram messaging. *Journal of Business Research*, 175. [CrossRef](#)
- Caliandro, A., Gandini, A., Bainotti, L., & Anselmi, G. (2024). The platformization of consumer culture: A theoretical framework. *Marketing Theory*, 0(0).
- Centola, D., Becker, J., Brackbill, D., and Baronchelli, A. (2018). Experimental evidence for tipping points in social convention. *Science*, 360(6393), 1116–1119.
- Chen, Z., and Berger, J. (2013). When, why, and how controversy causes conversation. *Journal of Consumer Research*, 40(3), 580–593.
- Chung, S., Shin, D. and Park, J. Predicting Firm Market Performance Using the Social Media Promoter Score. *Marketing Letters* 33, 545–561 (2022). [CrossRef](#)
- De Bruyn, A., and Lilien, G. L. (2008). A multi-stage model of word-of-mouth influence through viral marketing. *International Journal of Research in Marketing*, 25(3), 151–163.
- Dessart, L., Veloutsou, C., and Morgan-Thomas, A. (2015). Consumer engagement in online brand communities: A social media perspective. *Journal of Product and Brand Management*, 24(1), 28–42.
- Doyle, C., Sreenivasan, S., Szymanski, B. K., and Korniss, G. (2016). Social consensus and tipping points with opinion inertia. *Physica A: Statistical Mechanics and Its Applications*, 443, 316–323.
- Drenten, J., Gurrieri, L., Huff, A. D., and Barnhart, M. (2023). Curating a consumption ideology: Platformization and gun influencers on Instagram. *Marketing Theory*, 0(0).
- Dubé, J.-P. H., Hitsch, G. J., and Chintagunta, P. K. (2010). Tipping and Concentration in Markets with Indirect Network Effects. *Marketing Science*, 29(2), 216–249.
- Gerbersgagen, M. and Spath, S.A. (2023). Managers' Lived Experience with Technology in the Mortgage Industry, During the COVID-19 Pandemic. *International Journal of Management Science and Business Administration*, 9(3), 7-15.

- Gladwell, M. (2000). *The Tipping Point: How Little Things Can Make a Big Difference*. Little Brown.
- Goel, S., Anderson, A., Hofman, J., and Watts, D. J. (2015). The Structural Virality of Online Diffusion. *Management Science*, 62(1), 180–196. [CrossRef](#)
- Granovetter, M., and Soong, R. (1983). Threshold models of diffusion and collective behavior. *The Journal of Mathematical Sociology*, 9(3), 165–179.
- Gupta, S., Deodhar, S., Tiwari, A.A., Gupta, M. and Mariani, M. (2024). How consumers evaluate movies on online platforms? Investigating the role of consumer engagement and external engagement, *Journal of Business Research*, 176.
- Hanna, R., Rohm, A., and Crittenden, V. L. (2011). We're all connected: The power of the social media ecosystem. *Business Horizons*, 54(3), 265–273.
- Hausken, K. (2019), "A Game Theoretic Model of Adversaries and Media Manipulation," Games 10, 4, 1-15, Article 48.
- Hausken, K. (2020), Game Theoretic Analysis of Ideologically Biased Clickbait or Fake News and Real News, *Operations Research and Decisions* 30, 2, 39-57.
- Hausken, K. (2022), Theoretic Model of Adversaries and Media Manipulation: A Two-Period Extension, *International GameTheory Review* 24, 3, 2150019 [CrossRef](#)
- Hillerbrand, E. (2016). Semantic Web and Business: Reaching a Tipping Point? In M. Workman (Ed.), *Semantic Web: Implications for Technologies and Business Practices* (pp. 213–229). Springer International Publishing.
- Iles, I. A., Egnoto, M. J., Liu, B. F., Ackerman, G., Roberts, H., and Smith, D. (2017). Understanding the Adoption Process of National Security Technology: An Integration of Diffusion of Innovations and Volitional Behavior Theories. *Risk Analysis*, 37(11), 2246–2259.
- Jiang, L., Miao, Y., Yang, Y., Lan, Z., and Hauptmann, A. G. (2014). Viral Video Style: A Closer Look at Viral Videos on YouTube. *Proceedings of International Conference on Multimedia Retrieval*, 193–200.
- Johnson, W. (2012, September 3). Throw Your Life a Curve. *Harvard Business Review*.
- Jung, S., and Li, H. (2014). Global Production, Circulation, and Consumption of Gangnam Style. *International Journal of Communication*, 8, 2790-2810.
- Kalyanam, K., McIntyre, S., and Masonis, J. T. (2007). Adaptive experimentation in interactive marketing: The case of viral marketing at Plaxo. *Journal of Interactive Marketing*, 21(3), 72-85. [CrossRef](#)
- Kammer, A., Boeck, M., Hansen, J. V., and Hauschildt, L. J. H. (2015). The free-to-free transition: Audiences' attitudes toward paying for online news. *Journal of Media Business Studies*, 12(2), 107–120.
- Kawamoto, T., and Hatano, N. (2014). Viral spreading of daily information in online social networks. *Physica A: Statistical Mechanics and Its Applications*, 406, 34–41.
- King, R. A., Racherla, P., and Bush, V. D. (2014). What We Know and Don't Know about Online Word-of-Mouth: A Review and Synthesis of the Literature. *Journal of Interactive Marketing*, 28(3), 167-183.
- Kumar, V., and Mirchandani, R. (2012). Increasing the ROI of social media marketing. *MIT Sloan Management Review*, 54(1), 55–61.
- Lam, H.K.S., Yeung, A.C.L., Lo, C.K.Y., and Cheng, T.C.E. (2019). Should firms invest in social commerce? An integrative perspective. *Information and Management*. 56 (8).
- Lambert, A., Rome, A., and Fornari, F. (2023). Stayin' alive? Reflections on navigating digital dependency. *Marketing Theory*, 0(0). [CrossRef](#)
- Landsman, V., and Givon, M. (2010). The diffusion of a new service: Combining service consideration and brand choice. *Quantitative Marketing and Economics*, 8(1), 91–121.
- Langley, D. J., Hoeve, M. C., Ortt, J. R., Pals, N., and van der Vecht, B. (2014). Patterns of Herding and their Occurrence in an Online Setting. *Journal of Interactive Marketing*, 28(1), 16-25.
- Leitch, S., and Merlot, E. (2018). Power relations within brand management: The challenge of social media. *Journal of Brand Management*, 25(2), 85–92.
- Li, Y., Lai, C. and Lin, L. (2017). A diffusion planning mechanism for social marketing. *Information and Management* 54

(5), 638-650.

- Lin, L., Li, Y., and Wu, W. (2015). A social endorsing mechanism for target advertisement diffusion. *Information and Management*. 52(8), 982-997.
- Lin, X., Featherman, M. and Sarker, S. (2017). Understanding factors affecting users' social networking site continuance: A gender difference perspective. *Information and Management*. 54(3), 383-395.
- Lotka, A. J. (1924). *Elements of Mathematical Biology*. Dover Books.
- Mahajan, V., Muller, E., and Kerin, R. A. (1984). Introduction Strategy for New Products with Positive and Negative Word-of- Mouth. *Management Science*, 30(12), 1389–1404. [CrossRef](#)
- Malter, M.S., Holbrook, M.B., Kahn, B.E. The past, present, and future of consumer research. *Marketing Letters* 31, 137–149 (2020).
- Malthouse, E., and Shankar, V. (2009). A Closer Look into the Future of Interactive Marketing. *Journal of Interactive Marketing*, 23(2), 105-107.
- Mangold, W. G., and Faulds, D. J. (2009). Social media: The new hybrid element of the promotion mix. *Business Horizons*, 52(4), 357–365.
- Marchand, A., Hennig-Thurau, T. and Flemming, J. (2021) Social media resources and capabilities as strategic determinants of social media performance. *International Journal of Research in Marketing*, 38 (2), 549-571.
- Miles, C. (2014). The rhetoric of managed contagion: Metaphor and agency in the discourse of viral marketing. *Marketing Theory*, 14(1), 3-18.
- Moe, W. W., and Ratchford, B. T. (2018). How the Explosion of Customer Data Has Redefined Interactive Marketing. *Journal of Interactive Marketing*, 42(1), 1-2. [CrossRef](#)
- Mohan, S., and Punathambekar, A. (2019). Localizing YouTube: Language, cultural regions, and digital platforms. *International Journal of Cultural Studies*, 22(3), 317–333.
- Moldovan, S., Steinhart, Y., and Lehmann, D. R. (2019). Propagators, Creativity, and Informativeness: What Helps Ads Go Viral. *Journal of Interactive Marketing*, 47(1), 102-114.
- Mourdoukoutas, P., and Siomkos, G. J. (2009). *The Seven Principles of WOM and Buzz Marketing: Crossing the Tipping Point*. Springer Science and Business Media. [CrossRef](#)
- Njilla, L. Y., Pissinou, N., and Makki, K. (2016). Game Theoretic Modeling of Security and Trust Relationship in Cyberspace. *International Journal of Communication Systems*, 29(9), 1500-1512.
- Nurja, I. and Lahi, B. (2024). Introduction Economic and Psychological Well-Being During COVID-19 Pandemic in Albania, A Need for Sustainability. *International Journal of Management Science and Business Administration*, 10(3), 29-46.
- Obrenovic, B., Godinic, D., and Njavro, M. (2023). Sustaining company performance during the war-induced crisis using sourcing capability and substitute input. *Environment, Development and Sustainability*, 1-26.
- Obrenovic, B., Oblakovic, G., and Asa, A. R. (2024). Bibliometric Analysis of Financial and Economic Implications during the COVID-19 Pandemic Crisis. *Sustainability*, 16(7), 2897.
- Quesenberry, K. A., and Coolsen, M. K. (2019). Drama Goes Viral: Effects of Story Development on Shares and Views of Online Advertising Videos. *Journal of Interactive Marketing*, 48(1), 1-16.
- Rathore, A. K., Kar, A. K., and Vigneswara Ilavarasan P. (2017) Social Media Analytics: Literature Review and Directions for Future Research. *Decision Analysis* 14(4), 229-249. [CrossRef](#)
- Ravula, P., Bhatnagar, A., and Jha, S. (2024). Comparing the effectiveness of recommendation agents across devices. *International Journal of Information Management*, 76 0268-4012.
- Reichstein, T., and Brusch, I. (2019). The decision-making process in viral marketing—A review and suggestions for further research. *Psychology and Marketing*, 36(11), 1062-1081.

- Rogers, E. M. (2003). *Diffusion of innovations*. Free Press.
- Rosario, B., A., Russell, C. A., and Shanahan, D. E. (2022). Paradoxes of Social Support in Virtual Support Communities: A Mixed-Method Inquiry of the Social Dynamics in Health and Wellness Facebook Groups. *Journal of Interactive Marketing*, 57(1), 54-89.
- Savage, M. (2017, July 11). Gangnam Style is no longer the most-played video on YouTube. *BBC News*.
- Shakarian, P., Eyre, S., and Paulo, D. (2013). A Scalable Heuristic for Viral Marketing Under the Tipping Model. *ArXiv:1309.2963 [Physics]*.
- Singh, A., Dharamshi, N., Thimma Govarthanarajan, P., Samale, P. D., and Eirinaki, M. (2020). The Tipping Point In Social Networks: Investigating the Mechanism Behind Viral Information Spreading. *2020 IEEE Sixth International Conference on Big Data Computing Service and Applications (BigDataService)*, 54–61.
- Sriram, S., Manchanda, P., Bravo, M.E. Platforms: a multiplicity of research opportunities. *Marketing Letters* 26, 141–152 (2015).
- Testa, S., Massa, S., Martini, A. and Appio, A.F. (2020). Social media-based innovation: A review of trends and a research agenda. *Information and Management*. 57(3), 0378-7206.
- Taran, Z. (2012). The Seven Principles of WOM and Buzz Marketing: Crossing the Tipping Point. *Journal of Consumer Marketing*, 29(2), 163-164.
- Tiago, M. T. P. M. B., and Veríssimo, J. M. C. (2014). Digital marketing and social media: Why bother? *Business Horizons*, 57(6), 703–708.
- Tsai, W.-H. S., and Men, L. R. (2013). Motivations and Antecedents of Consumer Engagement With Brand Pages on Social Networking Sites. *Journal of Interactive Advertising*, 13(2), 76–87. [CrossRef](#)
- Vaghefi, M.S., Beheshti, N. and Jain, J. (2024). Dissemination of health messages in online social network: A study of healthcare providers' content generation and dissemination on Twitter. *Information and Management*. 61 (2).
- Verhulst, P. F. (1845). Recherches mathématiques sur la loi d'accroissement de la population. *Nouveaux Mémoires de l'Académie Royale Des Sciences et Belles-Lettres de Bruxelles*, 18, 3–38.
- Verma, D., Dewani, P.P., Behl, A. and Dwivedi, Y.K. (2023). Understanding the impact of eWOM communication through the lens of information adoption model: A meta-analytic structural equation modeling perspective. *Computers in Human Behavior*, 143.
- Vukanovic, Z. (2011). New Media Business Models in Social and Web Media. *Journal of Media Business Studies*, 8(3), 51–67.
- Winer, R. S. (2009). New Communications Approaches in Marketing: Issues and Research Directions. *Journal of Interactive Marketing*, 23(2), 108-117.
- Xiong, H., Payne, D., and Kinsella, S. (2016). Peer effects in the diffusion of innovations: Theory and simulation. *Journal of Behavioral and Experimental Economics*, 63, 1–13. [CrossRef](#)
- Yildirim, P., Wei, Y., Van den Bulte, C., and Lu, J. (2020). Social network design for inducing effort. *Quantitative Marketing and Economics*, 18(4), 381–417.
- Yoganarasimhan, H. (2012). Impact of social network structure on content propagation: A study using YouTube data. *Quantitative Marketing and Economics*, 10(1), 111–150.
- Yu, Y., Qiu, L., Chen, H. (2023). Movie fit uncertainty and interplay between traditional advertising and social media marketing. *Marketing Letters* 34, 429–448. [CrossRef](#)
- Zadeh, A. and Sharda, R. (2022). How Can Our Tweets Go Viral? Point-Process Modelling of Brand Content, *Information and Management*, 59 (2).
- Zhang, X. (2018). Frugal innovation and the digital divide: Developing an extended model of the diffusion of innovations. *International Journal of Innovation Studies*, 2(2), 53–64.
- Zhang, H., Wang, Z., Chen, S., and Guo, C. (2019). Product recommendation in online social networking communities: An empirical study of antecedents and a mediator. *Information and Management*. 56(2), 185-195.

- Zhou, T., and Zhang, S. (2009). Examining the Effect of E-commerce Website Quality on User Satisfaction. *2009 Second International Symposium on Electronic Commerce and Security, 1*, 418–421. [CrossRef](#)
- Zino, L., Ye, M., Mlakar, Z., Bolderdijk, J. W., Risselada, H., Fennis, B. M., and Cao, M. (2022). Incentivizing social diffusion on networks using a novel game-theoretic model.