Journal of Digital Marketing and Communication

Research Article
Volume 5(2), 2025, 96–113
https://doi.org/10.53623/jdmc.v5i2.719

Reciprocal Dynamics: How Ad-views and Ad-shares Reinforce Each Other

Chang-Won Choi

School of Journalism and New Media, University of Mississippi, USA

Correspondence: cchoi@olemiss.edu

SUBMITTED: 9 June 2025; REVISED: 14 July 2025; ACCEPTED: 21 July 2025

ABSTRACT: This study explores the reciprocal relationship between ad-viewing and ad-sharing in online video advertising and examines the moderating role of total likes. Drawing on two-step flow and social influence theories, it is hypothesized that daily ad-views drives daily ad-shares by reaching influencers, while daily ad-shares enhance daily ad-views through social and informational cues. Granger causality analysis of 392 YouTube advertisements reveals varying causal patterns, including reciprocal and unidirectional effects (ad-views → ad-shares and ad-shares → ad-views), with total likes amplifying these dynamics. These findings provide theoretical insights into viral advertising and practical implications.

KEYWORDS: Viral advertising; ad-viewing; ad-sharing; two-step flow; social influence

1. Introduction

In today's fast-paced digital landscape, video advertisements on platforms like YouTube can reach billions of users globally. Particularly, viral advertising, one of the most effective promotional activities, has transformed how brands achieve visibility. An advertisement often garnering millions of views within days through the power of social sharing. For instance, in 2020, Nike's *You Can't Stop Us* video advertisement (https://www.youtube.com/watch?v=WA4dDs0T7sM) achieved over 50 million views in just two weeks, demonstrating the powerful role of ad-sharing in boosting advertising effectiveness. Nonetheless, the mechanisms driving this phenomenon remain insufficiently understood.

Unlike traditional media, where advertising primarily involves passive consumption, digital platforms foster active user participation, such as liking, sharing, and commenting. This participatory nature provides new opportunities for engagement but also presents challenges, as users increasingly skip or block advertisements they perceive as intrusive [1–3]. In this context, ad-sharing has emerged as a promising strategy for overcoming these challenges. Because people are more inclined to watch video advertisements shared by those they trust [4,5], users who share advertisements can extend the advertising message to their networks, bypassing advertising avoidance mechanisms [5–7].

Despite growing interest in ad virality, most existing research conceptualizes the relationship between ad-sharing and ad-viewing as a unidirectional process where sharing leads to increased views [7–10]. However, this approach largely overlooks the possibility of reciprocal causality, a dynamic in which ad-viewing and ad-sharing influence each other over time in a feedback loop. In real-world settings, popular ads not only tend to be shared more, but those that are widely shared also tend to attract more views. This pattern suggests a mutually reinforcing relationship, where each behavior amplifies the other, yet this dynamic has received limited empirical attention in literature. As a result, several important questions remain unanswered: Do ad-views prompt ad-sharing? Or does ad-sharing drive ad-views? Do these effects reinforce each other, creating a virtuous cycle? Do like total likes amplify these relationships?

To address these questions, this study draws on two foundational frameworks: the two-step flow of communication [11] and social influence theory [12]. The two-step flow theory suggests that messages often reach broader audiences through influencers, who act as intermediaries in disseminating content. Extending this framework to online advertising, this study proposes that ad-viewing drives ad-sharing by increasing the likelihood of content reaching individuals predisposed to share, such as influencers or highly social users. In addition, social influence theory posits that shared content carry social proof, creating normative and informational pressures that drive subsequent views. For instance, when an advertisement is widely shared, it signals its relevance and quality, encouraging others to watch in order to conform to social norms [13].

Using a dataset of 392 YouTube video advertisements, this study examines the relationship between daily ad-views and ad-shares, as well as the moderating role of total likes. Employing Granger causality analysis, a statistical method used to determine whether one time series can predict another time series [14], the study identifies three possible patterns: (1) ad-views drive ad-shares, (2) ad-shares drive ad-views, and (3) both processes reinforce each other. While Granger causality does not establish true causation, it serves as a useful tool for inferring potential causal relationships between ad-viewing and ad-sharing based on time-series data. By moving beyond the unidirectional model of virality, these findings offer theoretical advancements and provide practical implications for optimizing the viral potential of online advertising.

2. Literature Reviews

2.1. The influence of ad-viewing on ad-sharing.

Advertising exposure serves as the foundation for consumers' cognitive, affective, and behavioral engagement with advertisements [15]. While not every viewer will share an advertisement, a higher number of ad-views increases the likelihood that it will reach individuals predisposed to sharing content such as highly social individuals, influencers, or those whose interests align with the ad's message.

The two-step flow of communication theory offers a valuable lens for understanding how ad-viewing influences ad-sharing. This theory posits that media messages often reach audiences indirectly, mediated by opinion leaders who filter and interpret the content before sharing it with their networks [11]. Opinion leaders, such as social media influencers or active sharers within communities, amplify the reach and impact of media messages by acting as intermediaries between the source and the general audience [16]. In the context of online advertising, these individuals play a pivotal role in extending the visibility and influence of video advertisements [17].

An advertisement's reach and impact can be further amplified when shared by key opinion leaders [18]. Additionally, individuals who are extroverted or open to new experiences are more likely to share video advertisements [19, 20]. Such opinion leaders and active sharers are particularly effective in driving advertisement engagement when they are perceived as authentic or when their values align with their audience's [21]. While initial exposure to an advertisement may occur through organic reach or targeted campaigns, its subsequent dissemination relies heavily on the ad-sharing behaviors of these influential users. As influencers or highly social users share the advertisement, they act as catalysts for broader engagement, triggering a cascading effect that extends the ad's visibility far beyond its direct audience [18].

Building on the two-step flow of communication theory, it is expected that a higher number of daily ad-views increases the likelihood of the ad reaching individuals inclined to share, thereby facilitating broader dissemination through their social networks.

H1. The number of daily ad-views will increase the number of daily ad-shares.

2.2. The influence of ad-sharing on ad-viewing.

Social influence theory posits that individuals' thoughts, attitudes, and behaviors are shaped by the actions and opinions of others [12]. This influence arises from various sources, including social norms, perceived consensus, and interactions within social groups [13, 22, 23].

Social influence operates through two primary mechanisms: informational or normative influence [24]. Informational influence occurs when people use others' input as evidence to refine their understanding, often leading to internalization, where individuals adopt behaviors or attitudes aligned with their values [23]. On the other hand, normative influence involves interpreting information from others as implied expectations for behavior, and this influence stems from processes of compliance or identification [25]. That is, individuals are inclined to conform to a group's beliefs both because they perceive the group as accurate (informational influence) and because they seek social acceptance (normative influence).

Previous studies have shown that social media platforms significantly amplify social influence dynamics through features such as likes and comments [22, 26, 27]. Although social influence theory has been applied to social media influencer research [21–23] and consumers' online buying behavior [28], it also provides a valuable framework for understanding the relationship between ad-sharing and ad-viewing.

When a video advertisement is shared, it reaches new audiences by leveraging the sharer's personal network, exponentially expanding exposure. This process aligns with normative influence, as frequent ad-sharing creates a perception of social norms around watching the content. Individuals are motivated to conform to these norms, seeking social acceptance or avoiding the fear of missing out (FOMO). For instance, sharing by close or trusted individuals signals shared values and mutual interests, increasing the likelihood that recipients will view the advertisement [4]. The act of sharing itself signals social approval, encouraging conformity to group behaviors and enhancing perceptions of the content as engaging or relevant [6, 29].

Informational influence can also play a critical role. Sharing by trusted sources, such as friends, family, or influencers, acts as an endorsement, signaling the video's quality and trustworthiness. Recipients interpret this behavior as a reliable cue about the value of the content, further motivating them to watch it.

Based on this theoretical foundation, ad-sharing is expected to serve as a powerful driver of ad-viewing by shaping perceptions of social relevance and informational credibility. Thus, the following hypothesis is proposed:

H2. The number of daily ad-shares will increase the number of daily ad-views.

2.3. Total likes as a catalyst.

According to Cha et al. [30], only 10% of YouTube videos account for more than 80% of the total views on the platform. This phenomenon, where certain content attracts disproportionate attention, has been observed across various domains, including online videos [31], online news [32], movies [33], and music [34]. Such a skewed distribution of attention highlights the role of mechanisms like social proof, normative biases, and algorithmic amplification in shaping audience behavior. Through this lens, we propose that the total number of likes plays a pivotal role in shaping the relationship between daily ad-views and daily ad-shares. Understanding this dynamic is essential for analyzing the spread of online content, particularly in the realm of viral advertising.

2.3.1. Total likes and the views-to-shares relationship.

The total number of likes can enhance the influence of daily ad-views on daily ad-shares by reinforcing the ad's perceived value and increasing its social appeal. High like counts serve as social proof, signaling the ad's popularity and perceived quality [35, 36]. Thus, a high level of total likes can trigger normative social influences, encouraging users to align with perceived social norms and collective approval. People are drawn to popular content not only because they perceive it as valuable, but also because engaging with widely endorsed material enhances their sense of belonging and social acceptance [37, 38].

Consequently, when an advertisement achieves substantial likes, viewers are more likely to feel that sharing it will reflect positively on them, showcasing their alignment with popular trends or signaling their discernment in identifying quality content. In this way, total likes amplify the likelihood of transforming passive viewership into active sharing behavior. Moreover, the synergistic interaction between likes and views fosters a sense of advertisement momentum. Users may perceive that by sharing highly liked content, they contribute to its growing popularity and relevance, enhancing their own sense of participation in a larger social movement [39]. Total likes, therefore, function as a catalyst, strengthening the influence of daily ad-views on daily ad-shares and ensuring that popular content continues to circulate widely.

2.3.2. Total likes and the shares-to-views relationship.

Total likes can strengthen the influence of daily ad-shares on daily ad-views by magnifying the perceived credibility and appeal of shared content. When users encounter an advertisement shared by others, the presence of a high number of likes may reinforce the ad's perceived quality and relevance [35, 38]. This dual signal, combining shares as personal endorsements and likes as collective approval, makes users more inclined to view the content [39]. High likes, in this sense, can enhance the persuasive impact of ad-shares by validating the shared content's worth.

This effect is particularly potent in environments where users rely on heuristics to navigate the overwhelming abundance of content [41]. In such scenarios, the combination of shares and likes acts as a shortcut for decision-making, signaling to users that the advertisement is entertaining, informative, or otherwise valuable [7, 42]. Total likes thereby enhance both the visibility and attractiveness of shared content, increasing the likelihood that it will be viewed by a broader audience [43].

Platform algorithms may further magnify this effect. High engagement metrics such as likes and shares are prioritized by recommendation systems, making the advertisement more visible in feeds, trending lists, and search results [44]. This algorithmic amplification creates a feedback loop: as shared content with high likes gains visibility, it attracts more views, which in turn further strengthens its engagement metrics. In this way, total likes serve as a key moderating factor that amplifies the effect of ad-shares on ad-views, ensuring the advertisement reaches a wider audience.

These insights suggest that total likes are not merely passive indicators of popularity but active social signals that shape user perception, engagement, and content visibility [45]. Specifically, when an advertisement has accumulated a high number of likes, the influence of daily ad-views on ad-shares may become stronger, as viewers perceive the content to be more socially validated and worth endorsing. Similarly, the effect of daily ad-shares on ad-views may be heightened since total likes reinforce the credibility and appeal of the shared content. Based on this reasoning, the following hypotheses are proposed:

H3. Higher total likes will increase the likelihood that daily ad-views influence daily ad-shares.

H4. Higher total likes will increase the likelihood that daily ad-shares influence daily ad-views.

Figure 1 presents the conceptual model.

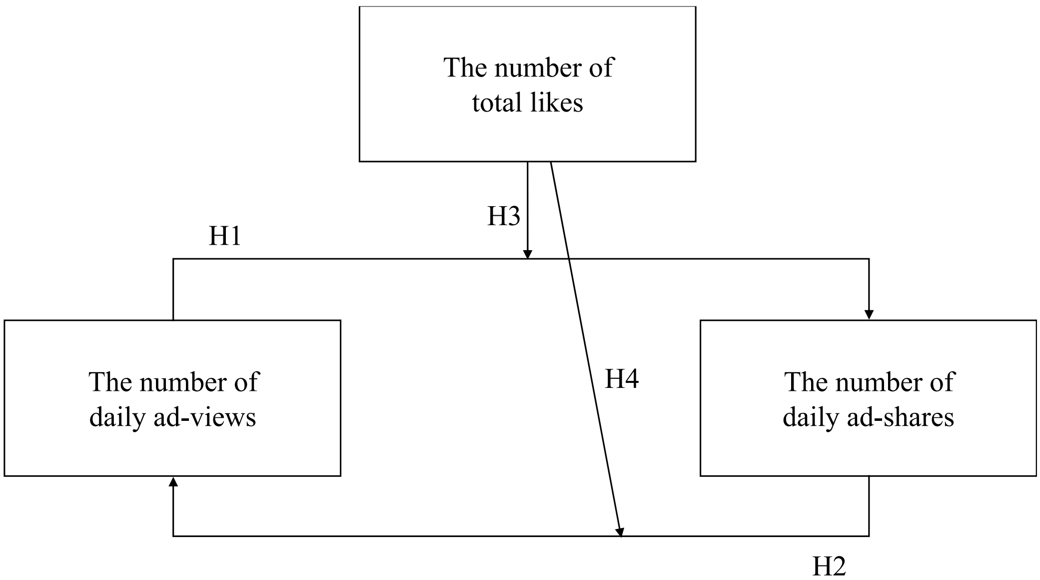

Figure 1. The conceptual framework.

3. Method

3.1. Brand selection.

We identified brand representatives with substantial investments in online video advertising. Specifically, all brands listed in the 2019 Leading National Advertisers Index [46] and the 2019 YouTube Ads Leaderboard were included in this study, ensuring the selection of prominent brands actively engaged in digital advertising. This process yielded a final sample of 45 brands across 11 product categories. Accordingly, metrics for all video advertisements published on the official YouTube channels of these 45 brands were collected.

3.2. Ad data collection.

To gather daily counts of views, shares, and likes for YouTube video advertisements uploaded between July and November 2020, three Python scripts were automatically executed on an Amazon Web Server at midnight (Eastern Time) each day from July to December 2020. First, video URLs published within the previous 24 hours were retrieved from each brand's U.S. or global YouTube channel using the YouTube Data API v3.0. These URLs were added to a master video list.

Second, based on the daily updated video list, video metadata such as view counts and likes was scraped daily from YouTube using the Python package BeautifulSoup. Third, since YouTube does not publicly provide information on video shares, share counts were collected separately from other sources. Social media posts containing the video advertisement URL were used to estimate the number of ad-shares.

Specifically, shares on Facebook were retrieved using the Facebook API v7.0, as Facebook is the second most popular social media platform among Americans after YouTube [47] and one of the primary platforms where YouTube videos are shared [48]. Additionally, shares on Twitter, Reddit, and Tumblr were collected using Brandwatch, a commercial social media analytics platform that aggregates publicly available data. Specifically, Brandwatch detects mentions and URL shares of YouTube videos across social platforms by monitoring publicly available posts that contain YouTube video links. While Brandwatch's tracking is limited to publicly accessible posts and may not capture private sharing (e.g., via email or direct messaging), it remains a useful tool for understanding the viral spread of ads across social platforms. Accordingly, Brandwatch has been widely adopted in academic research for social media monitoring and analysis [49].

Daily views and shares were calculated as the difference in cumulative counts from the previous day. From the processes outlined above, a total of 1,947 YouTube video advertisements published by 45 brands between July and November 2020 were collected.

3.3. Ad data collection.

The following criteria were applied to ensure the quality and reliability of the data for time-series analysis. First, each advertisement had to include at least 35 daily data points to conduct time-series analysis [50]. Thus, advertisements converted to private or made invisible within 35 days of publication were excluded. Consequently, the data collection period for video advertisements in the final dataset ranged from 36 to 71 days ($M = 51.8$, $SD = 8.5$), depending on availability.

Second, advertisements had to exhibit sufficient variance in share counts over time. Advertisements shared on social media for fewer than two days were excluded from the dataset. After applying these criteria, the final dataset consisted of 392 video advertisements from 41 brands (Table 1). The complete list of video advertisements can be found in the supplementary online material.

Table 1. Summary of the online video ad list

Categories	Number of Brands	Number of Video Ads
Apparel/Sportswear	3	31
Personal Care/Household	5	26
Technology	5	86
Telecommunications	3	27
Automotive	6	88
Beverage	7	25
Food	5	17
Furniture	1	1
Insurance	3	28
Retail	2	39
Non-Profit	1	24
Total	**41**	**392**

4. Results

4.1. Descriptive overview.

Over the 36 days, the shortest data collection period in the final dataset, a video advertisement was viewed on average 34,241 times per day (*SD* = 137,234.7; skewness = 7.1), shared 25.8 times per day (*SD* = 261.51; skewness = 17.4), and liked 3,964 times per day (*SD* = 23,248.7; skewness = 12.5). The distributions of these metrics were highly skewed (Supplementary Material A). Notably, 5% of the 392 YouTube video advertisements accounted for 74.7% of the total views, 90.4% of the total shares, and 82.5% of the total likes. During this period, the bottom 5% of advertisements were viewed 957 times or fewer, while the top 5% were viewed 5,604,541 times or more. Similarly, the bottom 5% of advertisements were shared 2 times or fewer, whereas the top 5% were shared 1,100 times or more. For likes, the bottom 5% of advertisements received 8 likes or fewer, while the top 5% received 18,050 likes or more.

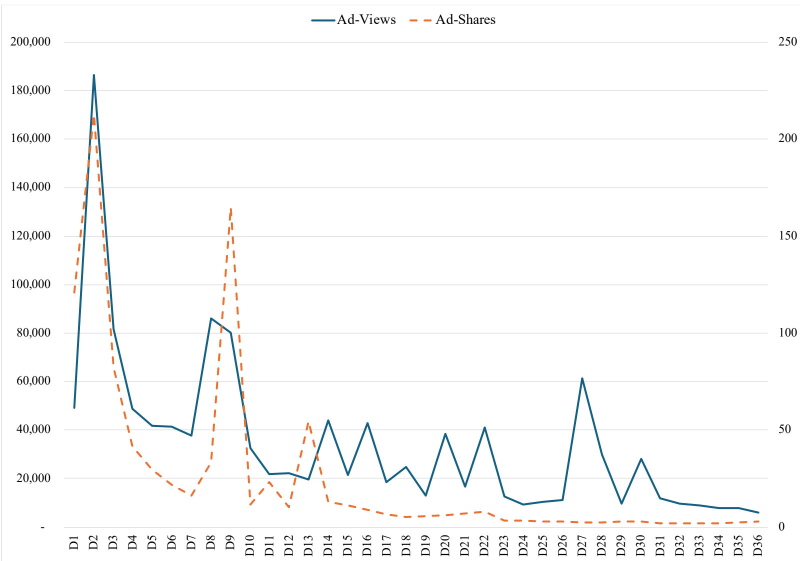

Figure 2. Trends in daily ad-views and ad-shares over time.
Note: daily ad-views (blue line, left y-axis) and ad-shares (orange dotted line, right y-axis)

Generally, both daily ad-views and ad-shares peaked within the first ten days, reflecting a surge of early interest and activity shortly after the advertisement's release. Specifically, both metrics reached their first peak on Days 1 and 2, followed by a second peak on Days 8 or 9. However, after Day 10, the patterns for views and shares began to diverge, suggesting that viewing and sharing behaviors do not always follow the same trajectory (Figure 2). These findings align with Broxton et al.'s [48] research, which shows that highly shared videos tend to generate views effectively over short periods, but this advantage in attracting views diminishes significantly over time. Additionally, the two observed peaks are consistent with Cheng et al.'s [51] study, which demonstrated that an initial burst in popularity can strongly trigger future re-bursts on social media. Taken together, unlike the reversed U-shaped patterns observed in the Product Life Cycle (PLC) and information diffusion, and virality follows an M-shaped pattern, a lifecycle characterized by two initial stages of steep growth followed by a decline. Supplementary Material B presents the trends in daily ad-views and ad-shares by major category.

4.2. Hypotheses testing.

To test H1 and H2, which examine the causal relationships between daily ad-views and daily ad-shares, a series of Granger time-series analyses were conducted for each of the 392 video ads. According to Granger causality [14], if the past values of variable x significantly improve the prediction of the present value of variable y compared to using only the past values of y, it can be said that x Granger-causes y. If both x Granger-causes y and y Granger-causes x, a reciprocal causal relationship exists between the two variables. Granger analysis has been widely applied in studies examining the effects of advertising expenditures and Facebook "Likes" on sales [52,53], as well as intermedia agenda-setting effects [54].

Granger time-series analysis requires data to meet the condition of stationarity, meaning the series must exhibit a constant mean and variance over time [54]. If data display seasonality, trends, or cycles, they are considered non-stationary. In this study, most vector autoregressions (VARs) of ad-views and ad-shares initially did not meet the stationarity condition. To address this, differencing was applied to remove trends by computing the difference between consecutive observations, as this method is effective for stabilizing the mean of time series with short-term interdependencies [55], such as those observed between ad-views and ad-shares [7]. When differencing was insufficient to achieve stationarity (e.g., in cases with persistent trends), de-trending was performed using linear regression to remove residual trends [55]. The sequence of applying differencing first, followed by de-trending, when necessary, was chosen to prioritize simpler transformations that address non-stationarity efficiently before using more complex methods. This approach also reflects the assumption that any underlying trends in ad-viewing or ad-sharing behaviors are likely to dissipate within a few days (addressed through differencing), rather than persist over longer periods such as weeks or months (requiring de-trending). For both ad-views and ad-shares, 341 cases were transformed using differencing, 47 cases required de-trending, and 4 cases met the stationarity condition without any transformation. After these transformations, stationarity was tested using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) procedures. All VARs for the 392 video advertisements met the stationarity requirement.

The time lag in the time-series analysis was determined using information criteria [56], including the Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQ), Schwarz

Criterion (SC), and Akaike's Final Prediction Error (FPE). The optimal lag was defined as the one yielding the smallest value across criteria. When the criteria suggested different lag lengths, AIC and FPE were prioritized due to their greater emphasis on predictive accuracy [56]. The analysis identified optimal lags ranging from one to seven days (M = 2.74, SD = 2.30), supporting the idea that ad-views and ad-shares influence each other within a short time frame [7].

A series of Granger analyses was conducted using the vars package in R. Out of 392 video advertisements, 103 (26.3%) exhibited a reciprocal causal relationship, in which daily ad-views influenced daily ad-shares and vice versa. 71 (18.1%) showed a unidirectional causal relationship from ad-views to ad-shares, while 50 (12.8%) showed the opposite direction, from ad-shares to ad-views. The remaining 168 advertisements (42.9%) showed no causal relationship between the two variables.

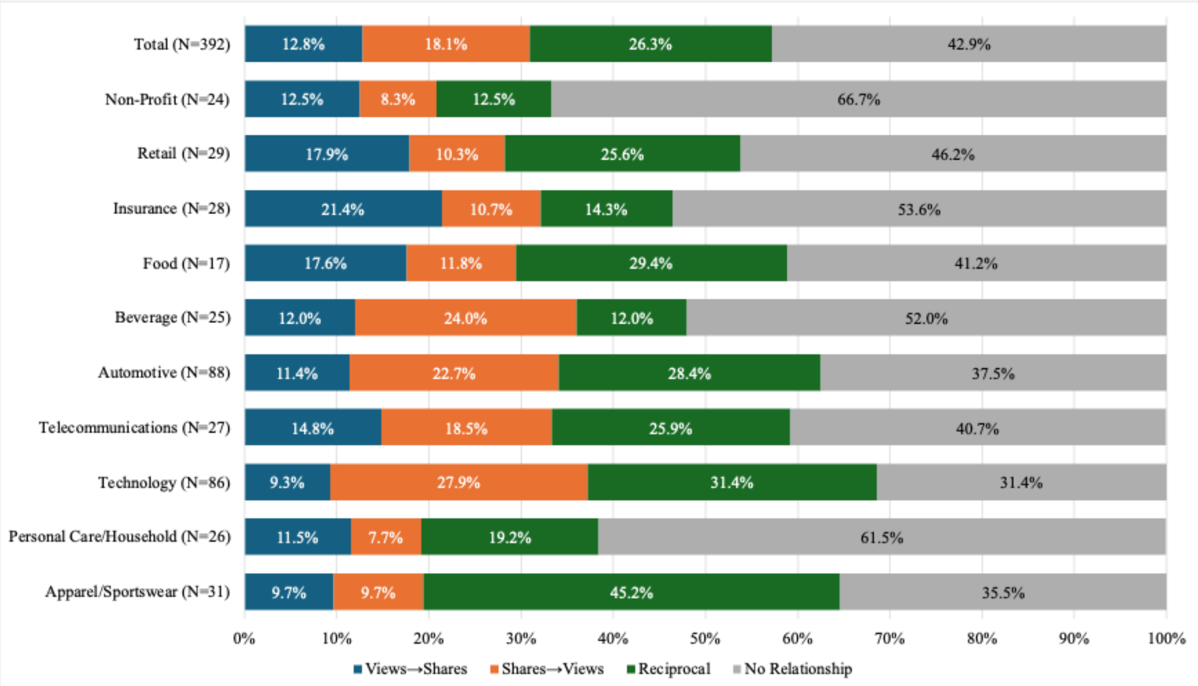

Figure 3. Relationship between ad-views and ad-shares across categories.

When broken down by industry category, notable differences emerged (Figure 3). First, the absence of any causal relationship was the most common pattern across all categories, suggesting that virality is far from guaranteed and may depend heavily on factors such as message quality, audience targeting, and platform algorithms. Nonetheless, advertisements in the apparel/sportswear and technology sectors showed a stronger prevalence of reciprocal relationships (45.2% and 31.4%, respectively). This may be because peer influence, social validation, and early adopter behavior play particularly important roles in these industries, where consumers often rely on social cues to evaluate trends, innovation, or brand relevance. These category-level insights suggest that reciprocal relationship is more likely to emerge in industries where social identity, innovation, and trend adoption are central to consumer decision-making.

To determine whether the proportions differed significantly across the Granger causality relationship types, a chi-square test was conducted. The results showed that the proportions were not equally distributed (χ^2 (3) = 81.2, p < .001). Subsequently, pairwise two-proportion z-tests were conducted to compare each of the four categories. As shown in Table 2, the 'No

Relationship' category had a significantly higher proportion than the 'Reciprocal' ($p < .001$) and both unidirectional categories: 'Views → Shares' ($p < .001$) and 'Shares → Views' ($p < .001$). Similarly, the 'Reciprocal' category had a significantly higher proportion than both unidirectional categories: 'Views → Shares' ($p < .05$) and 'Shares → Views' ($p < .001$). However, there was no significant difference between the two unidirectional relationships: Views → Shares' versus 'Shares → Views.'

Table 2. Pairwise comparisons: Granger causality relationships.

Frequencies		Z score	*p* values
Reciprocal Views→Shares	103 71	2.43	0.015
Reciprocal Shares→Views	103 50	4.28	< .001
Reciprocal No Relationship	103 168	-3.95	< .001
Views→Shares Shares→Views	71 50	1.91	0.056
Views→Shares No Relationship	71 168	-6.28	< .001
Shares→Views No Relationship	50 168	-8.00	< .001

In conclusion, the results suggest that while daily ad-views and daily ad-shares can influence each other, the most prevalent pattern observed was the absence of any causal relationship. Thus, H1 and H2 were partially supported. Additionally, no significant differences were found between the proportions of the 'Reciprocal,' unidirectional 'Views → Shares,' and unidirectional 'Shares → Views' relationships.

H3 and H4 examine whether the number of total likes influences the Granger causal relationships between daily ad-views and daily ad-shares. To test these hypotheses, a series of binary logistic regressions was conducted. The dependent variable for H3 was the presence of Granger causality from daily ad-views to daily ad-shares (as determined by H1 results). The dependent variable for H4 was the presence of Granger causality from daily ad-shares to daily ad-views (as determined by H2 results). The presence of Granger causality was coded as '1' if significant, and '0' if not. The predictor variable was the total number of likes during the data collection period.

Total likes were highly skewed (M = 4,890.5, SD = 26,258.3, Min = 0, Max = 42,4531; skewness = 11.7), which can lead to under- or overestimation of regression coefficients [57]. To address this, a log transformation was applied [58], reducing the skewness to 0.669.

As shown in Table 3, total likes had a significant effect on Granger causality in both directions: from daily ad-views to daily ad-shares ($B = 0.163$, Wald = 10.466, $p < 0.001$, Exp(B) = 1.177) and from daily ad-shares to daily ad-views ($B = 0.351$, Wald = 36.643, $p < 0.001$, Exp(B) = 1.420). The odds ratios, Exp(B), indicate that each one-unit increase in the natural log of total likes raised the odds of Granger causality by 17.7% in the views-to-shares direction and by 42.0% in the shares-to-views direction. These results suggest that total likes amplify the dynamic interplay between viewing and sharing behaviors, reinforcing the reciprocal feedback loop. Accordingly, both H3 and H4 were supported. Table 4 summarizes the results of all hypothesis tests.

Table 3. Results of the binary logistic regression.

	DV = Granger causality from daily ad-views to daily ad-shares			DV = Granger causality from daily ad-shares to daily ad-views		
	B	**Wald**	**Exp (*B*)**	***B***	**Wald**	**Exp (*B*)**
Constant	-1.365***	20.007	0.255	-2.172***	40.591	0.114
ln(T.Likes)	0.163***	10.466	1.177	0.351***	36.643	1.420
χ^2 (*df*)		10.845 (1) ***			44.367 (1) ***	
-2 Log likelihood		513.561			494.971	
Nagelkerke R^2		.037			.143	

Note: ln(T.Likes) represents the natural logarithm of the total number of likes; ****p* < .001.

Table 4. Summary of results.

	Relationship Tested	Support	Statistical Test	Significance
H1	Ad-views → Ad-shares	Partially supported	Granger causality	Significant in 39.0% of ads
H2	Ad-shares → Ad-views	Partially supported	Granger causality	Significant in 44.4% of ads
H3	Total likes moderating ‘ad-views → ad-shares’	Supported	Binary logistic regression	B = .163, $p < .001$
H4	Total likes moderating ‘ad-shares → ad-views’	Supported	Binary logistic regression	B = .351, $p < .001$

5. Discussion

This study explored the causal interplay between ad-viewing and ad-sharing in digital video advertising, with a focus on the moderating role of total likes. By integrating insights from two-step flow and social influence theories, the findings highlight the potential for dynamic and reciprocal relationships between these behaviors. Specifically, the results show that while ad-viewing can drive sharing by reaching key influences, ad-sharing can also foster further viewing by leveraging social proof and normative pressures. Total likes strengthened these relationships, creating a reinforcing cycle. These findings challenge traditional linear models of advertising dissemination, offering a more refined understanding of the complex, reciprocal processes that drive views, shares, and likes in digitally networked environments.

5.1. Theoretical implications.

This study makes several theoretical contributions to the literature on ad-views and ad-shares, providing new insights into the mechanisms that fuel the viral potential of online video advertising. By integrating two-step flow of communication theory [11] and social influence theory [12], the findings extend our understanding of how digital ads spread in the social media era.

First, unlike prior studies that primarily focused on the unidirectional influence of ad-sharing on ad-viewing [6,59,60], this study identifies three possible directions of causal relationships: (1) ad-views influencing ad-shares, (2) ad-shares influencing ad-views, and (3) a bidirectional relationship. Specifically, the study demonstrates that a reciprocal relationship can exist, supporting the idea that ad-sharing creates ripple effects through networks [9]. For instance, when a person shares an online video, their network may view the advertisement and share it again creating a chain reaction. This aligns with theoretical models of complex contagion and network effects, where feedback mechanisms accelerate the speed and scale of information diffusion [61]. Recognizing this cyclical dynamic expands existing theory beyond linear cause-and-effect frameworks in viral advertising research.

Second, this study extends the two-step flow theory by illustrating its application in online advertising. Traditionally, the theory suggests that media messages reach broader audiences through opinion leaders who act as intermediaries. The finding that ad-views significantly influenced daily ad-shares in 39.0% of video advertisements implies that targeting active sharers such as influencers or individuals who are extroverted and open to new experiences [19,20], can play a pivotal role in transforming passive ad-viewing into active ad-sharing behaviors [18,21]. This underscores the need for further research to identify and engage key sharers to boost campaign effectiveness.

Third, drawing from social influence theory, this study sheds light on how ad-sharing drives subsequent ad-viewing. When content is shared by friends or influencers, it not only signals shared values but also boosts perceptions of trust and credibility, encouraging recipients to watch [40,41]. Importantly, this research goes beyond prior studies' intention-based measures by leveraging actual behavioral data from platforms like Facebook, Twitter, Reddit, and Tumblr. The results revealed that ad-shares influenced ad-views in only 44.4% of the examined ads, suggesting that the widely held assumption that sharing inevitably increases exposure [5,7], is only partially accurate in real-world settings. This highlights the importance of identifying moderators that may either enhance or weaken this effect.

Fourth, the study demonstrates the moderating role of total likes in the relationship between ad-views and ad-shares. Total likes were found to amplify both the effect of views on shares (H3) and the effect of shares on views (H4). This finding supports the concept of social proof [35] where high like counts boost the perceived value of content and motivate individuals to engage. Moreover, the results suggest that likes act as a catalyst in a feedback loop higher engagement metrics lead to greater algorithmic visibility, which in turn leads to more views and shares [44]. These insights underscore the importance of likes not just as outcomes, but as active ingredients in the spread of digital advertising content.

5.2. Practical implications.

This study provides actionable insights for digital marketing professionals seeking to maximize the effectiveness of online video advertising through strategic management of engagement metrics. By demonstrating the reciprocal relationship between ad-viewing and ad-sharing, the findings suggest that advertisers should not treat views and shares as isolated metrics. Instead, they should be considered as mutually reinforcing behaviors that can be amplified through targeted strategies.

First, increasing early ad-view counts is critical for jumpstarting the sharing cycle, as it raises the likelihood that the advertisement will reach key opinion leaders and socially connected users who are more inclined to share content. In the initial phase of a campaign—typically the first two days, which corresponds to the initial peak shown in Figure 2, marketers should focus on building momentum by maximizing exposure among strategically targeted audiences. This early traction serves two important functions: it broadens the advertisement's reach to potential amplifiers, such as influencers and highly social users, and it enhances perceived relevance, which encourages further engagement among general viewers. To achieve this early visibility, advertisers rely on coordinated tactics such as strategic media placement on high-traffic digital platforms and initial paid promotion to boost exposure. These approaches increase the probability that the content will be encountered by users with a high propensity to share, thereby stimulating peer-to-peer dissemination. Once sharing begins, advertisement gains additional exposure, which in turn leads to more views, creating a cyclical pattern of engagement. This reciprocal relationship between viewing and sharing—identified in the present study—suggests that early investments in viewership can activate a self-reinforcing loop, where each behavior amplifies the other over time, ultimately enhancing the viral potential and longevity of the campaign.

Second, high like counts enhance the effectiveness of both views and shares by serving as a form of social proof that validates the content's appeal. Therefore, marketers should view "likes" as strategic assets that can reinforce the content's credibility and attractiveness. To encourage likes, brands should focus on emotionally resonant storytelling and use audience engagement tactics designed to prompt affective responses. Notably, prior research has shown that emotions are key drivers of "likes" on YouTube videos [62,63]. To actively increase likes—particularly in the early days of a campaign—marketers may collaborate with influencers to endorse and engage with the content immediately after launch. Such visible engagement can generate a bandwagon effect, prompting viewers to follow suit. Additionally, optimizing key video elements such as thumbnails, titles, and descriptions, with compelling visuals and relevant keywords can boost initial user interaction and raise the likelihood of likes. Since most digital platforms use engagement metrics, including likes, to determine content visibility, these early interactions can increase algorithmic exposure and help initiate the engagement loop identified in this study. By prioritizing early like-generation strategies, marketers can accelerate social validation and trigger a self-reinforcing cycle of views and shares, ultimately enhancing the ad's viral momentum.

Third, encouraging users to share through shareable content formats can significantly increase subsequent views by leveraging both normative and informational social influence. Sharing acts as a form of social proof and personal endorsement, enhancing the perceived relevance, credibility, and emotional resonance of the advertisement among the recipient's networks. To capitalize on this effect, marketers should embed clear calls-to-action within the video content itself, such as prompts to share, comment, or discuss. For instance, the *Dove Self-Esteem Project* ad invites parents to initiate a "selfie talk" with their children at the end of the video (https://www.youtube.com/watch?v=z2T-Rh838GAo), effectively turning passive viewing into interactive engagement. This type of design encourages sharing and amplifies message dissemination through meaningful interpersonal connections.

Finally, campaign performance should be evaluated holistically, not just based on reach or impressions. Advertisers should monitor the interaction between views, shares, and likes to identify which videos are entering a self-sustaining cycle of engagement. Understanding the directional dynamics and triggers of this cycle can inform real-time optimization decisions, such as increasing promotion for videos showing early signs of reciprocal momentum.

5.3. Limitations and future research.

This study possessed several limitations that could be addressed by future research. First, although Granger causality suggested predictive relationships between ad-views and ad-shares, it did not strictly examine causal relationships. Additionally, as the dataset used in this study relied on available online data [64], it did not account for the potential effects of other important factors, such as ad spending, and algorithmic recommendations on social media platforms, which could influence the relationship between ad-views and ad-shares. Future research should investigate causal relationships using experimental designs.

Second, due to privacy constraints, we could not account for the potential influence of the network size of individuals sharing an online video advertisement on social media. Sharing by users with large followings has a greater impact on others' exposure to a video advertisement compared to those with smaller networks. Future research should explore ways to measure or control for network size to better understand its effect on the relationship between ad-views and ad-shares.

Third, this study did not address the content characteristics of video advertisements within each directional relationship. Exploring the factors that influence the direction of these relationships—whether unidirectional (e.g., 'Views → Shares' or 'Shares → Views'), reciprocal, or absent—through content analysis of video advertisements would provide valuable insights. Notably, in this study, 42.9% of video advertisements exhibited no relationship between views and shares. Therefore, future research should explore not only the factors that promote relationships between these variables but also those that inhibit them. Particularly, understanding the underlying content, contextual, and temporal factors that shape these divergent trajectories could significantly refine models of digital ad engagement. For example, when and why do cyclical view–share dynamics emerge, given that some ads go viral, others remain stagnant, some build momentum gradually, and others peak quickly before fading? Addressing these questions would help refine our understanding of how and why engagement loops take hold or fail to cross different types of video advertisements.

Funding Statement

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2022S1A5C2A03093660).

Author Contribution

The author solely conducted the conceptualization, methodology, data collection, analysis, writing, and revision of this manuscript.

Competing Interest

The researcher has declared there is no competing interest in this research.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.53623/jdmc.v5i2.719.

References

[1] Goodrich, K.; Schiller, S.Z.; Galletta, D. (2015). Consumer reactions to intrusiveness of online-video advertisements. *Journal of Advertising Research*, *55*(1), 37–50. https://doi.org/10.2501/JAR-55-1-037-050.

[2] Li, H.; Edwards, S.M.; Lee, J.-H. (2002). Measuring the intrusiveness of advertisements: Scale development and validation. *Journal of Advertising*, *31*(2), 37–47. https://doi.org/10.1080/00913367.2002.10673665.

[3] McCoy, S.; Everard, A.; Polak, P.; Galletta, D.F. (2008). An experimental study of antecedents and consequences of online ad intrusiveness. *International Journal of Human–Computer Interaction*, *24*(7), 672–699. https://doi.org/10.1080/10447310802335664.

[4] Hayes, J.L.; King, K.W.; Ramirez, A. (2016). Brands, friends, & viral advertising: A social exchange perspective on the ad referral processes. *Journal of Interactive Marketing*, *36*, 31–45. https://doi.org/10.1016/j.intmar.2016.04.001.

[5] Porter, L.; Golan, G.J. (2006). From subservient chickens to brawny men: A comparison of viral advertising to television advertising. *Journal of Interactive Advertising*, *6*(2), 4–33. https://doi.org/10.1080/15252019.2006.10722116.

[6] Cho, S.; Huh, J.; Faber, R.J. (2014). The influence of sender trust and advertiser trust on multistage effects of viral advertising. *Journal of Advertising*, *43*(1), 100–114. https://doi.org/10.1080/00913367.2013.811707.

[7] Tellis, G.J.; MacInnis, D.J.; Tirunillai, S.; Zhang, Y. (2019). What drives virality (sharing) of online digital content? The critical role of information, emotion, and brand prominence. *Journal of Marketing*, *83*(4), 1–20. https://doi.org/10.1177/0022242919841034.

[8] Fernandes, J.; Segev, S. (2024). The persuasion cues that make video advertising go viral: A conceptual replication and extension comparing viral vs. Non-viral advertising. *Journal of Marketing Communications*, 1–27. https://doi.org/10.1080/13527266.2024.2376918.

[9] Hayes, J.L.; King, K.W. (2014). The social exchange of viral ads: Referral and coreferral of ads among college students. *Journal of Interactive Advertising*, *14*(2), 98–109. https://doi.org/10.1080/15252019.2014.942473.

[10] McDuff, D.; Berger, J. (2020). Why do some advertisements get shared more than others? *Journal of Advertising Research*, *60*(4), 370–380. https://doi.org/10.2501/JAR-2020-027.

[11] Katz, E.; Lazarsfeld, P.F. (1955). Personal influence: The part played by people in the flow of mass communications. Free Press: Los Angeles, USA.

[12] Raven, B.H. (2008). The bases of power and the power/interaction model of interpersonal influence. *Analyses of Social Issues and Public Policy*, *8*(1), 1–22. https://doi.org/10.1111/j.1530-2415.2008.00159.x

[13] Cialdini, R.B.; Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annual Review of Psychology*, *55*, 591–621. https://doi.org/10.1146/annurev.psych.55.090902.142015.

[14] Granger, C.W.J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*(3), 424–438. https://doi.org/10.2307/1912791.

[15] Eisend, M.; Tarrahi, F. (2016). The effectiveness of advertising: A meta-meta-analysis of advertising inputs and outcomes. *Journal of Advertising*, *45*(4), 519–531. https://doi.org/10.1080/00913367.2016.1185981.

[16] Hunt, K.; Gruszczynski, M. (2024). "Horizontal" two-step flow: The role of opinion leaders in directing attention to social movements in decentralized information environments. *Mass Communication and Society*, *27*(2), 230–253. https://doi.org/10.1080/15205436.2023.2167663.

[17] Ha, L.; Yang, Y. (2023). Research about persuasive effects of social media influencers as online opinion leaders 1990-2020: A review. *International Journal of Internet Marketing and Advertising*, *18*(2–3), 220–241. https://doi.org/10.1504/IJIMA.2023.129661.

[18] Cha, M.; Haddadi, H.; Benevenuto, F.; Gummadi, K. (2010). Measuring User Influence in Twitter: The Million Follower Fallacy. *Proceedings of the International AAAI Conference on Web and Social Media*, *4*(1), Article 1. https://doi.org/10.1609/icwsm.v4i1.14033.

[19] Choi, C.-W. (2020). The impacts of consumer personality traits on online video ads sharing intention. *Journal of Promotion Management*, *26*(7), 1073–1092. https://doi.org/10.1080/10496491.2020.1746468.

[20] Kulkarni, K.K.; Kalro, A.D.; Sharma, D. (2019). Sharing of branded viral advertisements by young consumers: The interplay between personality traits and ad appeal. *Journal of Consumer Marketing*, *36*(6), 846–857. https://doi.org/10.1108/JCM-11-2017-2428.

[21] Tafesse, W.; Wood, B.P. (2022). Social media influencers' community and content strategy and follower engagement behavior in the presence of competition: An Instagram-based investigation. *Journal of Product & Brand Management*, *32*(3), 406–419. https://doi.org/10.1108/JPBM-02-2022-3851.

[22] Mulcahy, R.; Barnes, R.; de Villiers Scheepers, R.; Kay, S.; List, E. (2024). Going viral: Sharing of misinformation by social media influencers. *Australasian Marketing Journal*, 14413582241273987. https://doi.org/10.1177/14413582241273987.

[23] Ouvrein, G.; Pabian, S.; Giles, D.; Hudders, L.; De Backer, C. (2021). The web of influencers. A marketing-audience classification of (potential) social media influencers. *Journal of Marketing Management*, *37*(13–14), 1313–1342. https://doi.org/10.1080/0267257X.2021.1912142.

[24] Deutsch, M.; Gerard, H.B. (1955). A study of normative and informational social influences upon individual judgment. *The Journal of Abnormal and Social Psychology*, *51*(3), 629–636. https://doi.org/10.1037/h0046408.

[25] Kelman, H.C. (2006). Interests, Relationships, identities: Three central issues for individuals and groups in negotiating their social environment. *Annual Review of Psychology*, *57*, 1–26. https://doi.org/10.1146/annurev.psych.57.102904.190156.

[26] Holvoet, S.; Hudders, L.; Herrewijn, L. (2022). The power of Facebook friends: An investigation of young adolescents' processing of social advertising on social networking sites. *Communications*. https://doi.org/10.1515/commun-2021-0044.

[27] Seo, Y.; Kim, J.; Choi, Y.K.; Li, X. (2019). In "likes" we trust: Likes, disclosures and firm-serving motives on social media. *European Journal of Marketing*, *53*(10), 2173–2192. https://doi.org/10.1108/EJM-11-2017-0883.

[28] Bhukya, R.; Paul, J. (2023). Social influence research in consumer behavior: What we learned and what we need to learn? – A hybrid systematic literature review. *Journal of Business Research*, *162*, 113870. https://doi.org/10.1016/j.jbusres.2023.113870.

[29] De Bruyn, A.; 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. https://doi.org/10.1016/j.ijresmar.2008.03.004.

[30] Cha, M.; Kwak, H.; Rodriguez, P.; Ahn, Y.-Y.; Moon, S. (2007). I Tube, You Tube, Everybody Tubes: Analyzing the World's Largest User Generated Content Video System, IMC '07: Proceedings of the 7th ACM SIGCOMM conference on Internet measurement, San Diego, California, USA, October 24 – 26; Dovrolis, C.; Roughan, M. Eds.; New York, NY. https://doi.org/10.1145/1298306.1298309.

[31] Fu, W.W.; Sim, C.C. (2011). Aggregate bandwagon effect on online videos' viewership: Value uncertainty, popularity cues, and heuristics. *Journal of the American Society for Information Science and Technology*, *62*(12), 2382–2395. https://doi.org/10.1002/asi.21641.

[32] Knobloch-Westerwick, S.; Sharma, N.; Hansen, D. L.; Alter, S. (2005). Impact of popularity indications on readers' selective exposure to online news. *Journal of Broadcasting & Electronic Media*, *49*(3), 296–313. https://doi.org/10.1207/s15506878jobem4903_3

[33] Xu, X.; Fu, W.W. (2014). Aggregate bandwagon effects of popularity information on audiences' movie selections. *Journal of Media Economics*, *27*(4), 215–233. https://doi.org/10.1080/08997764.2014.963229.

[34] Salganik, M.J.; Dodds, P.S.; Watts, D.J. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, *311*, 854–856. https://doi.org/10.1126/science.1121066.

[35] Cialdini, R.B. (2008). Influence: Science and Practice, 5th ed.; Allyn and Bacon: Boston, USA.

[36] Lim, H.; Bright, L.F.; Wilcox, G.B. (2022). Is repetition really the key to success? The impact of ad repetition and the power of "Likes" on Facebook. *Journal of Interactive Advertising*, *22*(3), 238–248. https://doi.org/10.1080/15252019.2022.2106327.

[37] Escalas, J.E.; Bettman, J.R. (2005). Self-construal, reference groups, and brand meaning. *Journal of Consumer Research*, *32*(3), 378–389. https://doi.org/10.1086/497549.

[38] Venema, T.A.G.; Kroese, F.M.; Benjamins, J.S.; de Ridder, D.T.D. (2020). When in doubt, follow the crowd? Responsiveness to social proof nudges in the absence of clear preferences. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.01385.

[39] Bakshy, E.; Rosenn, I.; Marlow, C.; Adamic, L. (2012). The role of social networks in information diffusion. *Proceedings of the 21st International Conference on World Wide Web*, 519–528. https://doi.org/10.1145/2187836.2187907.

[40] Sundar, S.S. (2008). The MAIN model: A heuristic approach to understanding technology effects on credibility. In Digital Media, Youth, and Credibility; Metzger M.J., Flanagin, A.J., Eds.; The MIT Press: Cambridge, USA, pp. 73–100.

[41] Metzger, M.J.; Flanagin, A. J.; Medders, R. B. (2010). Social and heuristic approaches to credibility evaluation online. *Journal of Communication*, *60*(3), 413–439. https://doi.org/10.1111/j.1460-2466.2010.01488.x.

[42] Sundar, S.S.; Nass, C. (2001). Conceptualizing sources in online news. *Journal of Communication*, *51*(1), 52–72. https://doi.org/10.1111/j.1460-2466.2001.tb02872.x.

[43] Weng, L.; Menczer, F.; Ahn, Y.-Y. (2013). Virality prediction and community structure in social networks. *Scientific Reports*, *3*(1), 2522. https://doi.org/10.1038/srep02522.

[44] Matamoros-Fernández, A.; Gray, J. E.; Bartolo, L.; Burgess, J.; Suzor, N. (2021). What's "Up Next"? Investigating algorithmic recommendations on YouTube across issues and over time. *Media and Communication*, *9*(4), 234–249. https://doi.org/10.17645/mac.v9i4.4184.

[45] Fuchs, C. (2021). Social Media: A Critical Introduction. Sage Publications.

[46] Leading National Advertisers 2020 Fact Pack. (accessed on 1 May 2025) https://s3-prod.adage.com/whitepapers/leading-national-advertisers-2020-fact-pack.html.

[47] Share of U.S. adults using social media, including Facebook, is mostly unchanged since 2018. (accessed on 1 May 2025) https://www.pewresearch.org/fact-tank/2019/04/10/share-of-u-s-adults-using-social-media-including-facebook-is-mostly-unchanged-since-2018/.

[48] Broxton, T.; Interian, Y.; Vaver, J.; Wattenhofer, M. (2013). Catching a viral video. *Journal of Intelligent Information Systems*, *40*(2), 241–259. https://doi.org/10.1007/s10844-011-0191-2.

[49] Hayes, J.L., Britt, B.C., Evans, W., Rush, S.W., Towery, N.A., & Adamson, A.C. (2021). Can social media listening platforms' artificial intelligence be trusted? Examining the accuracy of Crimson Hexagon's (Now Brandwatch consumer research's) AI-driven analyses. *Journal of Advertising, 50*(1), 81–91. https://doi.org/10.1080/00913367.2020.1809576.

[50] Becketti, S. (2013). Introduction to Time Series Using Stata, 1st ed;. Stata Press: Texas, USA.

[51] Cheng, J., Adamic, L.A., Kleinberg, J.M., & Leskovec, J. (2016). Do Cascades Recur? Proceedings of the 25th International Conference on World Wide Web, 671–681. https://doi.org/10.1145/2872427.2882993.

[52] Brettel, M.; Reich, J.-C.; Gavilanes, J.M.; Flatten, T. C. (2015). What drives advertising success on Facebook? An advertising-effectiveness model. *Journal of Advertising Research*, *55*(2), 162–175. https://doi.org/10.2501/JAR-55-2-162-175.

[53] Hsu, M.K.; Darrat, A.F.; Zhong, M.; Abosedra, S.S. (2002). Does advertising stimulate sales or mainly deliver signals? A multivariate analysis. *International Journal of Advertising*, *21*(2), 175–195. https://doi.org/10.1080/02650487.2002.11104925.

[54] Vargo, C.J.; Guo, L.; Amazeen, M.A. (2018). The agenda-setting power of fake news: A big data analysis of the online media landscape from 2014 to 2016. *New Media & Society*, *20*(5), 2028–2049. https://doi.org/10.1177/1461444817712086.

[55] Brockwell, P.J.; Davis, R.A. (2016). Introduction to Time Series and Forecasting, 3rd ed.; Springer: Cham, Switzerland.

[56] Pfaff, B. (2008). Analysis of Integrated and Cointegrated Time Series with R; Springer New York, USA.

[57] Kline, R.B. (2016). Principles and Practice of Structural Equation Modeling, 4th ed.; The Guilford Press: New York, USA.

[58] Dunn, P.K.; Smyth, G K. (2018). Generalized Linear Models with Examples in R. Springer: New York, USA..

[59] Chiu, H.-C.; Hsieh, Y.-C.; Kao, Y.-H.; Lee, M. (2007). The determinants of email receivers' disseminating behaviors on the internet. *Journal of Advertising Research*, *47*(4), 524–534. https://doi.org/10.2501/S0021849907070547.

[60] Hayes, J.L.; Shan, Y.; King, K.W. (2018). The Interconnected role of strength of brand and interpersonal relationships and user comment valence on brand video sharing behaviour. *International Journal of Advertising*, *37*(1), 142–164. https://doi.org/10.1080/02650487.2017.1360576.

[61] Watts, D.J.; Dodds, P.S. (2007). Influentials, networks, and public opinion formation. *Journal of Consumer Research*, *34*(4), 441–458. https://doi.org/10.1086/518527.

[62] Munaro, A.C.; Hübner Barcelos, R.; Francisco Maffezzolli, E.C.; Santos Rodrigues, J.P.; Cabrera Paraiso, E. (2021). To engage or not engage? The features of video content on YouTube affecting digital consumer engagement. *Journal of Consumer Behaviour*, *20*(5), 1336–1352. https://doi.org/10.1002/cb.1939.

[63] Kujur, F.; Singh, S. (2018). Emotions as predictor for consumer engagement in YouTube advertisement. *Journal of Advances in Management Research*, *15*(2), 184–197. https://doi.org/10.1108/JAMR-05-2017-0065.

[64] Malthouse, E.C.; Li, H. (2017). Opportunities for and pitfalls of using big data in advertising research. *Journal of Advertising*, *46*(2), 227–235. https://doi.org/10.1080/00913367.2017.1299653.