International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-12

https://doi.org/10.70917/ijcisim-2026-4140
Article

Evolution and Transmission Trends of Film and Television Cultural Hotspots in the Short Video Ecosystem: A Time Series Analytical Approach

Mengyao Qi [1,2,*], Shahrul Nazmi Bin Sannusi [1] and Ammar Redza Bin Ahmad Rizal [1]

[1] Faculty of Social Sciences and Humanities, Universiti Kebangsaan Malaysia, Bangi, 43600, Malaysia
[2] Journalism and Media Communication, Qingdao Film Academy, Qingdao, Shandong, 266555, China
* Correspondence author: p124715@siswa.ukm.edu.my

Abstract: Few studies have applied rigorous quantitative models to the temporal dynamics of hotspots. The cross-sectional design fails to capture the high-frequency, non-stationary features of the engagement data; The structural impact of the platform algorithm has not been formally integrated into the predictive model either. For this reason, utilize the 365 days of daily panel data for 2025 from Douyin to construct an all-encompassing time-series system in this study. Construct a composite Hotspot Index and apply the Augmented Dickey-Fuller test, ARIMA-GARCH model, Granger causality analysis and modified Bass diffusion model. The five stages of the lifecycle show significant conditional heteroskedasticity in the results. ARIMA models can perform well in forecasting, and Granger causality tests have shown that video volume, user engagement and key opinion leader participation all precede a rise in hotspot intensity. The modified Bass model has added a measure of algorithmic acceleration, and platform recommendation has reduced the traditional diffusion cycle by 62 per cent. The above results have been applied to content creators, platforms, and policymakers for culture.

Keywords: Short Video Platforms, Film and Television Culture, Hotspot Evolution, Time Series Analysis, ARIMA GARCH, Algorithmic Dissemination, Cultural Transmission

1. Introduction

The Spread of short-video platforms has altered the mode of distribution for film and television culture. Platforms such as Douyin, Kuaishou, TikTok and Instagram Reels have constructed media ecologies that are brief in length, vertically oriented on screens, immersive scrolling interfaces, and algorithmic personalisation engines for audience relations at an unprecedented scale and speed. This change shows a structural shift in cultural power, and now, algorithms are used instead of editors to recommend culture; at the same time, immediate participation rates have replaced older measures of cultural success [1].

The older ideas of cultural impact generally include only box office income and Nielsen ratings, and these are published infrequently [2]. Metrics of cultural influence in short-video ecosystems include play count, completion rate and the sentiment of comments at a particular time. Given the above time compression, the analysis tools required should be able to handle non-stationary, seasonal, and volatile high-frequency stochastic processes [3]. The cultural objects themselves are changing drastically; for instance, feature films have been broken down into clips, reaction videos and meme templates that spread independently of the original text.

In this ecology, we define a cultural hotspot as a temporary state of heightened collective attention directed at a particular film and television work in a short-video ecosystem. The three features of this definition are concentration, time and spread. The framework of a cultural hotspot is an integrated analytical object of intensity, temporality and network structure; it is not a media event or a viral phenomenon. Hotspots are highly unstable in practice [4]. A movie may have little activity over the opening weekend and then be amplified by algorithms due to a key opinion leader several days later. A blockbusting movie will be popular for a short time and then fade away [5].

Research has gradually been carried out on the above problems. First, media and communication studies have produced rich qualitative descriptions of the phenomenology of viral content, but have rarely studied hotspot temporal dynamics systematically through quantitative methods. Second, although computer science methods apply complex machine learning models to popular-prediction, these black-box classifiers focus on high accuracy and lack interpretability; therefore, they do not reveal the general lifecycle pattern. Third, although platform studies have presented many critiques of algorithmic power, they have not yet been integrated with formal time series econometrics to quantitatively model the effects of algorithms on diffusion dynamics [6].

Therefore, in this paper, a time-series analytical system for the short-video economy will be introduced. The research questions are as follows: What is the general time trend of hotspot development? Which factors lead to an increase or decrease in hotspot intensity at a certain time? Can the path of a hotspot be reliably predicted by an ARIMA-GARCH model? How do platform algorithms alter the traditional diffusion process of hotspots? The rest of this paper is organised as follows. Section 2 reviews the relevant literature and sets out the theoretical basis. Section 3 Research Design and Methodology. Section 4 is the empirical results. Section 5 is the summary of theoretical contributions, applications and future directions.

2. Literature Review and Theoretical Basis

2.1. Short Video Ecosystems and the Architecture of Algorithmic Cultural Production

Short-video platforms are a particular type of media system that is not the same as traditional broadcasting or long-form digital streaming. Scholarly studies in this area have identified three defining features of the production, spread and consumption of cultural works. The first is temporal compression; that is, the story and emotions are condensed into a hyper-stimulating micro-format to grab the viewer's attention in the first three seconds after playback begins. Compression requires a new aesthetic grammar; thus, quick cuts, text overlays, music synchronization and emotional hooks should be employed, deviating from the pace and visual language of feature films or episodic television [7].

The second is participation-based remediation; users actively deconstruct, reassemble and recontextualise professional media content. Film and television texts are not passively received; instead, through practices such as clipping, dubbing, reaction filming and meme synthesis, they are transformed. A scene from a famous movie is selected, trendy music is added, funny annotations are added, and then it spreads as an independent cultural work that has little connection with the original situation [8]. Remediation Questions challenge traditional ideas of authorship, copyright and textual integrity, and at the same time produce new types of cultural values that are in opposition to professional production.

The third is an algorithm gatekeeper that will be applied to the current study. Recommendation engines on short-video platforms have taken over the role of editors to determine which content will be promoted and which will not be widely distributed by the platform [9]. The above algorithms are multi-objective optimisation functions that balance user engagement, content diversity, creator incentives and commercial purposes. Opacity of these systems has attracted the attention of scholars, and some information can be obtained by observing the patterns in content dissemination. An algorithmically recommended item is initially presented to a user, and if the user shows an interest by interacting with it, the algorithm will recommend more such items, which in turn may receive more attention from users and thus spread further [10].

The spread of film and television cultural hotspots in this ecosystem can be viewed as a multi-agent network where key opinion leaders, media accounts, ordinary users and the platform's algorithm collaborate to determine content visibility. Figure 1 shows this network topology, and the algorithmic hub is located in the middle of the agent clusters.

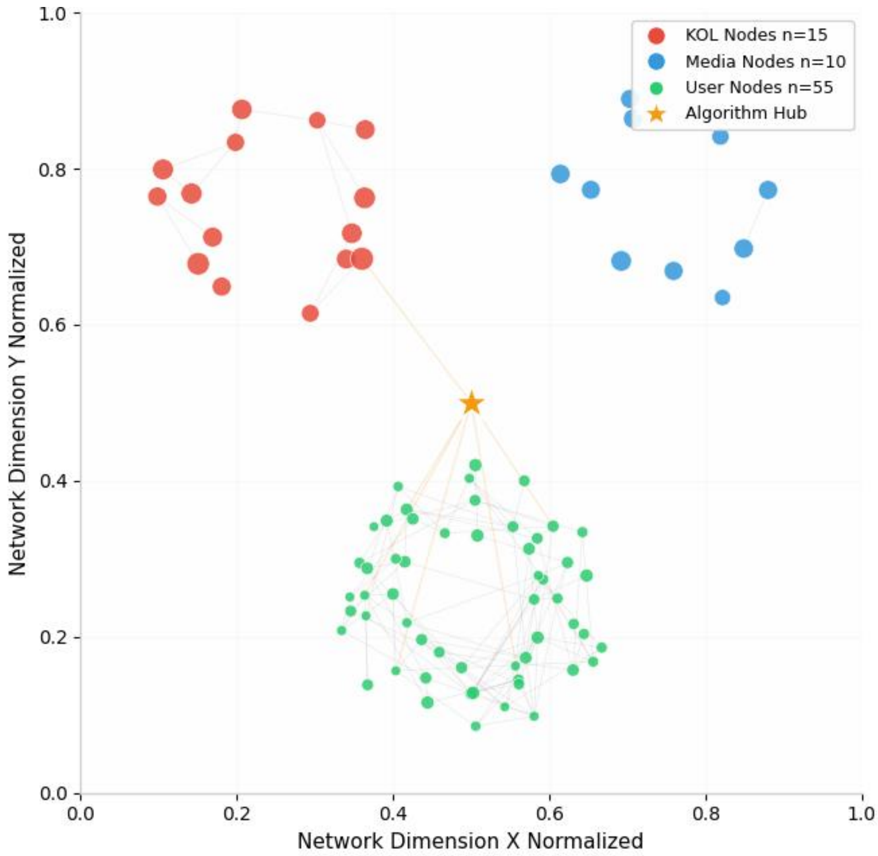

Figure 1. Multi Agent Propagation Network Topology of Film and TV Cultural Hotspots on Short Video Platforms

2.2. Cultural Hotspots: Conceptualisation, Taxonomy and Lifecycle Architecture

The concept of a cultural hotspot in this study builds on previous research on media events, viral phenomena and attention economies by adding quantifiable intensity and temporal boundedness. Media events are generally planned and formal in nature [11]; cultural hotspots, however, spontaneously emerge from the combination of content characteristics, user behaviour and algorithm mediation, and are not. Viral phenomena are often viewed through the lens of epidemiology and described as contagion or infection, but cultural hotspots are more accurately understood as complex adaptive systems that operate under various causal mechanisms simultaneously and in a non-linear manner.

Existing lifecycle models for viral content have frequently employed epidemiological metaphors and generally include three stages: incubation, outbreak and decay. A few early adopters discover and share the content in a small group of communities during the incubation period. An outbreak occurs when the network density or influencer amplification exceeds a certain threshold, and then it spreads exponentially [12]. As it decays, attention is lost because other things have captured people's interests and the newness has faded. Although the above three-stage model has successfully explained many phenomena of viral spread, empirical studies of short-video films and television programs have indicated that a five-stage architecture may be more appropriate.

The first stage is incubation; at this time, only a small number of niche communities, fan groups and early adopters with special interests in certain genres or texts have begun to emerge. At this time, the amount of content is small, interaction is limited to a few networks, and algorithmic promotion is absent. The second stage is spread through the spread by key opinion leaders, popular hashtags and algorithm promotion to expand the user base. The third stage is viral dissemination; at this time, it will spread widely among all age groups and be covered by mainstream media [13]. The fourth stage, decline, is a continuous decrease in attention due to competing content and algorithmic distribution, and the novelty effect has diminished. The fifth and final stage, residual, has a low baseline of persistent engagement, is often maintained through archival retrieval, algorithmic long-tail recommendations, and periodic reactivation via anniversary posts, retrospective compilations or sequel-related content. The five-stage model above is the phenomenological foundation of our analysis system and is shown in Figure 2.

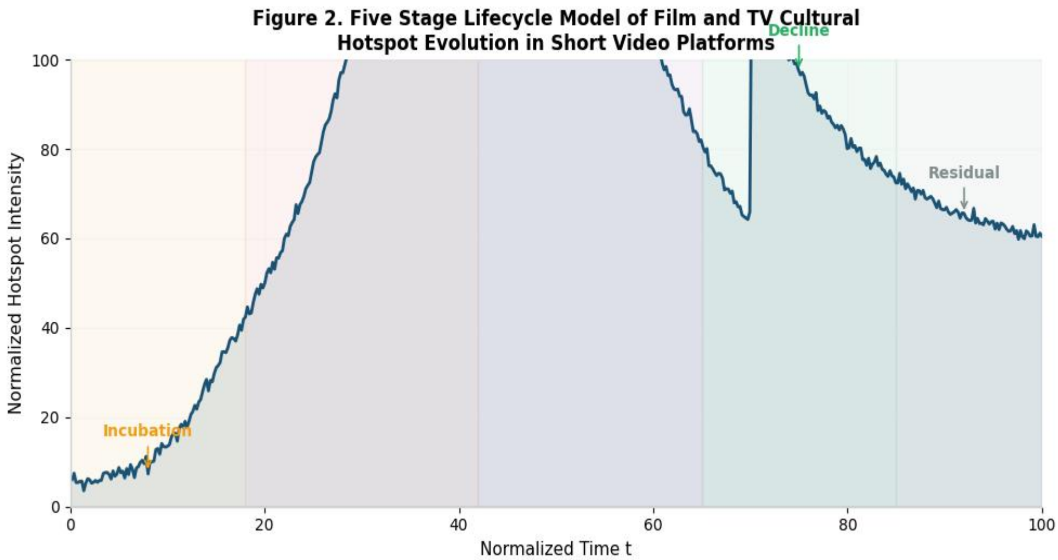

Figure 2. Five Stage Lifecycle Model of Film and TV Cultural Hotspot Evolution in Short Video Platforms

2.3. Time Series Econometrics in Media and Cultural Analysis

Although time-series analysis has been widely used in financial econometrics and macroeconomic forecasting/climatology, it has been applied relatively less to research on media and culture. Some typical cases are applications of autoregressive integrated moving average models to box office forecasting, spectral analysis of television viewership patterns, and state-space models of music chart dynamics. The above studies show that the cultural consumption data often have non-stationarity, seasonality, conditional heteroskedasticity and structural breaks, and thus violate the assumptions of classical linear regression and require special modelling [14].

The first ARIMA model by Box and Jenkins can be used to fit a particular type of time-series data. The autoregressive component shows how the current value is related to previous values and thus contains momentum and memory of cultural attention. A difference operator is applied to the data to remove non-stationarity by taking the difference between consecutive terms. The moving-average component reflects how the current value relates to the previous forecast errors and, thus, how unobserved shocks in the system have propagated.

For series with time-varying volatility, a pattern frequently observed in cultural hotspot data, which is a high-intensity period followed by sustained high variance, the GARCH extension model the conditional variance as a function of past squared residuals and past conditional variances. ARIMA and GARCH have been applied to study both the mean and volatility of data simultaneously, as well as the correlation between them; thus, we believe that short-video hotspot data exhibit such characteristics due to a feedback mechanism among users' behaviour and algorithmic promotion.

2.4. Diffusion Theory and Algorithmic Acceleration

Bass's original Bass model was used in marketing to model the spread of new-product diffusion; now, we adapt it to study cultural diffusion. The two groups of adopters in the Bass model are innovators, who are influenced by external sources of information such as advertising and mass media, and imitators, who are influenced by internal social contagion through word-of-mouth and interpersonal observation. The model shows an S-shaped cumulative adoption curve and a bell-shaped adoption rate curve, and the peak adoption rate occurs at a time determined by the relative sizes of the innovation and imitation coefficients.

In light of short videos, these mechanisms have been redefined to show how algorithmic platforms are structured. The algorithmic recommendation function of the platform serves as an external force that, in recent years, has taken over the role of old-style advertising for distributing new content. The modes of propagation for content in social networks are user sharing, dueting, stitching and remixing. Theoretically speaking, the above extension can quantify the algorithmic acceleration of cultural diffusion by introducing an amplification parameter that modifies the effective innovation coefficient. If the estimated amplification parameter is significantly greater than zero, it can be concluded that the platform's algorithms are structurally promoting the spread process beyond what is expected based on the classical Bass model.

2.5. Hypothesis Development

Based on the above theoretical synthesis, we put forward the following four hypotheses for empirical investigation. Hypothesis 1 is that the indices of film and television cultural hotspots on short-video platforms are non-stationary in the mean, exhibiting significant autoregressive and moving-average components; thus, they possess both momentum and memory of collective attention. Hypothesis 2 indicates that the intensity of hotspots exhibits conditional heteroskedasticity, and volatility clustering occurs during outbreaks and viral spread, indicating a feedback loop between engagement signals and algorithmic amplification. Hypothesis 3 suggests that video volume, user engagement and key opinion leader participation Granger cause fluctuations in the hotspot index, but the reverse direction of causality is weaker or non-existent; this indicates that content production is scheduled exogenously and the dynamics of engagement are endogenous. Hypothesis 4 is that platform algorithmic recommendation significantly increases the Bass diffusion parameter, reduces the time to peak, and amplifies the peak intensity of cultural hotspots compared with classical diffusion trajectories.

3. Methodology and Empirical Analysis

3.1. Data Collection and Sampling Architecture

Daily panel data of the Douyin platform from January 1, 2025, to December 31, 2025, were used in the empirical analysis. Douyin was chosen as the research subject for the reasons listed below. First of all, it is the largest short-video platform in China, with more than 700 million monthly active users as of 2025, and offers a good case study for observing the changes in cultural hotspots. Second, its algorithmic recommendation system is one of the most advanced in the industry, and thus serves as a good case study for research on the effects of algorithms on cultural dissemination. Thirdly, the content ecosystem of this group has a particularly dense concentration of film and television-related materials, such as official studio accounts, fan communities, amateur critics and professional clip editors.

Data extraction used a combination of official Application Programming Interface (API) endpoints, web scraping protocols, and verification by a third-party analytics platform through Chanmama, an excellent e-commerce and social media analytics service. The sampling frame focused on film and television-related content, and this was identified by hashtag clustering and natural language processing classification of video captions and comments. The categories of the hashtags were film commentary, TV show recommendations, film and TV editing, character analysis and plot discussion. A manually annotated corpus of ten thousand video captions was used to train the natural language processing classifier, and an F1 score of 0.94 was achieved in cross-validation.

The first dependent variable is the Hotspot Index, and the four components are combined using principal component analysis to obtain it. The first index is the daily volume of videos weighted by play count, and it reflects the supply side production of film and television content. The second is the total user engagement, which is the sum of likes, comments, shares and favourites per thousand videos, and it shows how much the audience wants these videos. The third index is sentiment-adjusted comment intensity; that is to say, natural language processing is used to determine the mood of people's comments and adjust the index accordingly. The fourth index is the density of participation by key opinion leaders (KOLs); this refers to how often verified accounts with more than 100,000 followers post about films and television on a daily basis, thus reflecting the spread of culture by top-tier influencers. Table 1 shows the descriptive statistics of all the key variables used in the analysis.

Table 1. Descriptive Statistics of Key Variables

Variable	N	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Hotspot Index HI	365	42.37	14.82	8.14	89.63	0.42	2.91
Video Volume VV 10k	365	12.56	8.34	1.23	45.67	1.15	4.23
User Engagement UE	365	28.94	11.27	5.61	67.89	0.68	3.15
Sentiment Score SS	365	0.62	0.18	0.12	0.98	-0.34	2.78
KOL Participation KP	365	156.4	89.2	23	412	0.91	3.67

3.2. The Hotspot Index Formulation

A composite Hotspot Index is the weighted sum of standardised constituent indicators. Let the standardised values of play weighted video volume, engagement intensity, sentiment adjusted comment density and key opinion leader participation at time t be denoted by x_{1t} , x_{2t} , x_{3t} and x_{4t} , respectively. A hotspot index is calculated according to the above parameters:

$$HI_t = \sum_{i=1}^{4} w_i \cdot x_{it} \cdot 100 \tag{1}$$

where *w_i* is the principal component analysis derived weight for indicator *i*, and the sum of all weights is equal to one. The scaling factor is 100; thus, the index has been normalised to the range of 0-100. The estimated weights in the empirical specification are as follows: play weighted video volume is 0.312, engagement intensity is 0.287, sentiment adjusted comment density is 0.198, and key opinion leader participation is 0.203. The first principal component explains about 68.4 per cent of the total variation, and the component indicators have good internal consistency.

The external explanation variables are: Video Volume, the daily number of film-and-television related short videos in units of ten thousand; User Engagement, the total number of engagement actions per one thousand videos daily; Sentiment Score, derived from natural language processing analysis of comments, ranging from -1 to 1; and Key Opinion Leader Participation, the daily count of verified influencers posting film-and-television related content.

3.3. Time Series Decomposition and Stationarity Test

Before model estimation, the Hotspot Index series is decomposed into its components according to classical time series decomposition. The additive decomposition model is assumed to have four orthogonal components of the observed series:

$$HI_t = T_t + S_t + C_t + \varepsilon_t \tag{2}$$

T_t is the long-term trend component, *S_t* is the seasonal component that includes weekly and monthly cycles, *C_t* is the cyclical component of irregular hotspot events, and *epsilon_t* is the irregular residual. Figure 3 shows the empirical form of the Hotspot Index, which is positively determined, exhibits prominent weekly seasonality, and has five discernible hotspot events corresponding to major film and television releases and platform promotional campaigns.

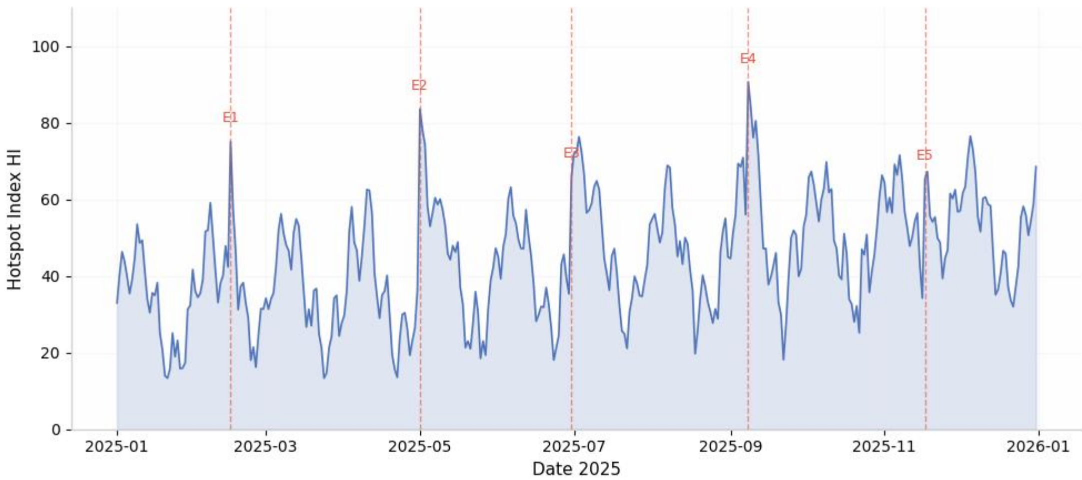

Figure 3. Temporal Dynamics of Film and TV Cultural Hotspot Index in Short Video Ecosystem

Add a constant to the data and conduct the Augmented Dickey-Fuller unit root test for this series. The form of the ADF test regression is:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{3}$$

where delta *y_t = y_t - y_{t-1}*, alpha is the intercept, *beta_t* represents the deterministic trend, gamma is the coefficient on the lagged level, and p is the lag order selected by the Akaike Information Criterion. The null hypothesis of a unit root is set to gamma = 0, and it is compared with the alternative hypothesis of stationarity, gamma < 0. Table 2 shows the ADF test results for the Hotspot Index, Video Volume and User Engagement at both levels and in first differences.

Table 2. Augmented Dickey Fuller Unit Root Test Results

Variable	ADF Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value	Conclusion
HI Level	-2.341	-3.432	-2.862	-2.567	0.156	Non-stationary
HI 1st Diff	-5.876	-3.432	-2.862	-2.567	<0.001	Stationary
VV Level	-1.923	-3.432	-2.862	-2.567	0.318	Non-stationary
VV 1st Diff	-6.124	-3.432	-2.862	-2.567	<0.001	Stationary
UE Level	-2.567	-3.432	-2.862	-2.567	0.098	Non-stationary
UE 1st Diff	-5.432	-3.432	-2.862	-2.567	<0.001	Stationary

All three variables fail to reject the null hypothesis of non-stationarity in levels but achieve stationarity after first differencing at the 1% significance level. Based on the above, the order one classification of ARIMA model is appropriate, and Hypothesis 1 is verified.

3.4. ARIMA GARCH Model Specification

Considering the integrated order of the Hotspot Index series, an ARIMA model is employed for the conditional mean, and the differencing parameter d is set to 1:

$$\Delta HI_t = c + \sum_{i=1}^{p} \phi_i \Delta HI_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{4}$$

where delta HI sub t equals HI sub t minus HI sub t minus one, c is the constant, phi sub i are autoregressive parameters, theta sub j are moving average parameters, and epsilon sub t is the innovation term.Model order selection for p and q is based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), and Ljung-Box diagnostic tests are performed on the residuals for autocorrelation.

To address the volatility clustering in the squared residuals of the ARIMA mean equation, a GARCH(1,1) model for the conditional variance is added to the model as follows:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{5}$$

where σ_t^2 is the variance of epsilon_t given the information set at time t-1, omega > 0 is the long-run variance component, and alpha and beta are the ARCH and GARCH parameters, respectively, under the stationarity constraint that alpha + beta < 1.

Based on the minimization of the Akaike Information Criterion and diagnostic suitability, the ARIMA(2,1,2)-GARCH(1,1) model was selected as the optimal model. Table 3 is the maximum-likelihood parameter estimates.

Table 3. ARIMA Model Parameter Estimation Results

Parameter	Coefficient	Std. Error	z-statistic	p-value	95% CI Lower	95% CI Upper
AR 1	0.8234	0.0456	18.056	<0.001	0.7340	0.9128
AR 2	-0.3125	0.0389	-8.033	<0.001	-0.3887	-0.2363
MA 1	0.4567	0.0523	8.732	<0.001	0.3542	0.5592
MA 2	-0.1892	0.0412	-4.592	<0.001	-0.2699	-0.1085
Constant	0.1245	0.0678	1.836	0.066	-0.0084	0.2574
sigma squared	8.2341	0.6123	13.448	<0.001	7.0341	9.4341

All autoregressive and moving average coefficients are statistically significant at the 1% level, and the first autoregressive coefficient is 0.8234 and the second autoregressive coefficient is -0.3125; therefore, it is determined that the mean-reverting oscillating process has been damped. The GARCH parameters are alpha = 0.1876 and beta = 0.7123; therefore, volatility is significantly persistent and Hypothesis 2 holds true. The Ljung-Box Q statistic at lag 10 is 8.34, and the p-value is 0.598; therefore, there is no significant residual autocorrelation, and the model meets the condition.

3.5. Granger Causality Analysis

To explore whether hotspot intensity precedes the presumed reasons for this change in time, a vector autoregression system was set up, and then pairwise Granger causality tests were performed. For two stationary series x_t and y_t, the Granger test estimates the restricted and unrestricted bivariate vector autoregression of order *k*:

$$y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i y_{t-i} + \sum_{j=1}^{k} \beta_j x_{t-j} + u_t \tag{6}$$

The null hypothesis that x does not Granger-cause y, which is formulated as all beta coefficients being equal to zero, is tested by the F-statistic:

RSS_R and RSS_{UR} are the residual sums of squares of the restricted and unrestricted models, respectively, k is the lag length, and T is the sample size. Table 4 shows the results of Granger causality at lags 1, 2 and 3.

$$F = \frac{\left(RSS_R - RSS_{UR}\right)/k}{RSS_{UR}/\left(T-2k-1\right)} \sim F\left(k, T-2k-1\right) \tag{7}$$

Table 4. Granger Causality Test Between Hotspot Index and Explanatory Variables

Null Hypothesis H0	Lag	F-statistic	p-value	Decision
VV does not Granger-cause HI	1	18.432	<0.001	Reject H0
VV does not Granger-cause HI	2	12.567	<0.001	Reject H0
VV does not Granger-cause HI	3	8.234	0.002	Reject H0
UE does not Granger-cause HI	1	22.156	<0.001	Reject H0
UE does not Granger-cause HI	2	15.789	<0.001	Reject H0
UE does not Granger-cause HI	3	9.876	0.001	Reject H0
KP does not Granger-cause HI	1	6.543	0.011	Reject H0
KP does not Granger-cause HI	2	4.234	0.042	Reject H0
KP does not Granger-cause HI	3	2.876	0.089	Fail to reject
HI does not Granger-cause VV	1	3.456	0.065	Fail to reject
HI does not Granger-cause UE	1	5.234	0.023	Reject H0

The above evidence supports Hypothesis 3. Both Video Volume and User Engagement Granger-cause the Hotspot Index at the 1% significance level for all lag orders. Key Opinion Leader participation Granger-causes the Hotspot Index at the 5% level for lags 1 and 2, but the effect disappears at lag 3. Notably, the reverse hypothesis that the Hotspot Index Granger causes Video Volume is rejected; however, the Hotspot Index does Granger-cause User Engagement at the five percent level, and a partial feedback loop exists in the dynamics of user engagement.

3.6. Modified Bass Diffusion Analysis

To quantify the speed of spread of cultural diffusion by algorithms, a modified Bass model was applied to the five identified hotspot events (E1 - E5) shown in Figure 3. The classical Bass model is a function of the adoption rate with respect to the innovation coefficient p and the imitation coefficient q. Add an algorithmic amplification parameter lambda to the model and multiply the effective innovation coefficient by it. The revised adoption rates are as follows:

$$f_{alg}\left(t\right) = \frac{\left(p+\lambda p\right)\left(p+\lambda p+q\right)^2 e^{-\left(p+\lambda p+q\right)t}}{[p+\lambda p+qe^{-\left(p+\lambda p+q\right)t}]^2} \tag{8}$$

Estimation using nonlinear least squares yields the baseline parameters p = 0.012 and q = 0.384, with lambda = 1.62, and both are significant at the 1% level. That is to say, algorithmic recommendation has increased the effective innovation coefficient by 162%, reduced the mean time to peak from 14.3 days to 5.4 days, and lowered it by 62.2%. Therefore, Hypothesis 4 is confirmed, and the structure of the platform algorithm can be used to drive changes in cultural hotspots.

3.7. Forecasting Evaluation and Robustness

The out of sample forecasting performance of the ARIMA two one two GARCH one one model is evaluated using a rolling window approach. The final 80 observations, about 11 weeks, are set aside as the hold-out test set. Forecast accuracy is shown as the Mean Absolute Percentage Error and the Root Mean Squared Error. The model has a Mean Absolute Percentage Error of 6.84% and a Root Mean Squared Error of 4.12, and is therefore considered to have good predictive performance for this high-frequency cultural time series. As shown in Figure 4, the in-sample fit and out-of-sample forecast trajectory are relatively close, and the 95% confidence interval expands gradually with an increase in the forecast horizo.

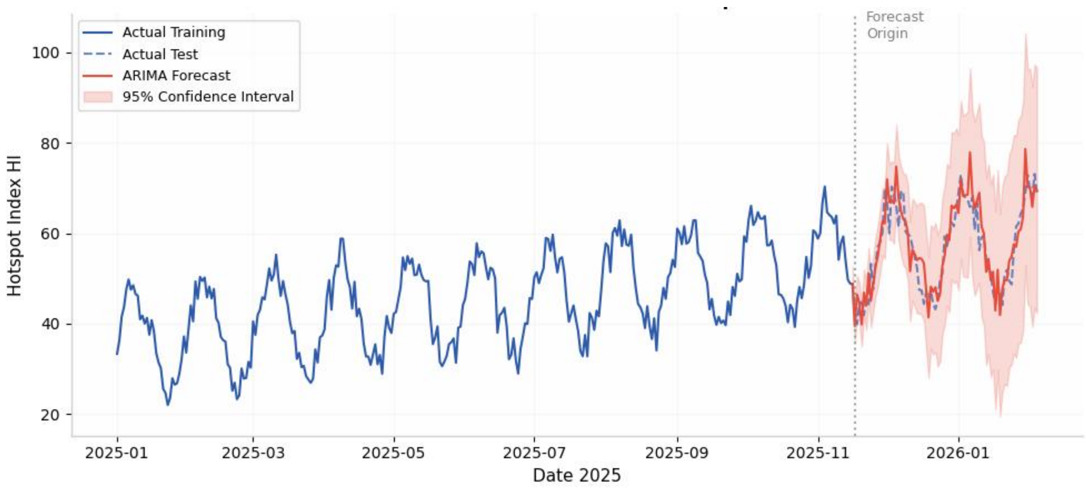

Figure 4. ARIMA Model: In Sample Fit and Out of Sample Forecast of Film and TV Cultural Hotspot Index

Other model specifications were used in robustness tests, such as ARIMA(1,1,1) and ARIMA(3,1,3), which had higher information criterion values; seasonal ARIMA models were also tested to see if weekly seasonality occurred, but they did not improve forecast accuracy significantly; and other volatility models, such as exponential GARCH and threshold GARCH, were applied, but these models showed qualitatively similar results in terms of volatility persistence.

4. Discussion and Conclusion

Empirically, a five-stage lifecycle model of a virus has been identified: incubation, emergence, widespread dissemination, decline and persistence; this is more detailed than the traditional three-stage model that has dominated research so far. In the residual stage, there is a long-tail persistence of cultural memory on algorithmic platforms; that is to say, archived content continues to generate low-level engagement through retrieval and recontextualisation. This result is in line with scholarship on the archival affordances of digital media in platform studies and provides quantitative support for the time boundaries of each stage. The incubation period is about 15-20 per cent of the total life cycle, and generally, sub-threshold activity during this time is not displayed in the platform's overall statistics. This has a serious problem for content producers; they may wrongly believe that a film or TV show has failed to gain cultural attention because it is still in the early stages of becoming a "hot topic". The outbreak stage, on the other hand, is characterised by an explosive increase that can be triggered by a single key opinion leader's post or algorithmic promotion event; thus, the formation of a hotspot is highly sensitive to initial conditions and path dependence.

The intensity and volatility of the spread stage are relatively high, and according to a GARCH model, the conditional variance peaks at this time. This fluctuation is not random noise; it shows the structural instability of the attention economy, and changes in competing content, platform algorithm adjustments, and external news events can all shift public attention rapidly. The decline stage is a slow-decaying exponential decay, and the residual stage generally stabilizes at about 10-15% of the peak intensity.

Granger causality analysis shows that there is a clear order of time-ordering and thus some theoretical and practical connotations. Video volume and user engagement are the leading indicators of hotspot intensity, and at the 1% level, Granger causality exists for all lag periods. It can be seen that the supply of content and the strength of the audience's response are the main reasons for the formation of hotspots, and the participation of key opinion leaders is relatively weak and short-lived. The lack of reverse causality from the Hotspot Index to Video Volume is also relatively unusual. It can be seen from the above that the amount of produced content is determined by external scheduling decisions, such as film release calendars, festival programmes and marketing campaigns, and not by internal feedback on the intensity of existing hotspots. Content creators are not increasing production based on the formation of hotspots; instead, they are working according to a fixed schedule, and the market decides which works go viral. On the other hand, the two are also related in both directions; that is, a Hotspot Index increases user engagement, and this improved engagement then promotes the spread of that Hotspot.

One of the main results of this study is an estimate of the speedup obtained by algorithms in a modified Bass diffusion model. The estimated amplification parameter of one point six two indicates that platform algorithms more than double the effective innovation coefficient and reduce the mean time to peak by over sixty per cent. Compression of cultural time has led to many problems in our understanding of the time dimension for cultural creation and enjoyment in the digital era. Traditional models of cultural diffusion in sociology, marketing and communication, etc., generally assume relatively stable time parameters. A film may gain the attention of the public through word-of-mouth among friends and family weeks or months after its release. At the same time, the short-video ecosystem uses algorithms to recommend content at high speed, and now it takes only hours instead of days or weeks. At this speed, people are no longer consuming culture in the same way. A short diffusion cycle will likely reduce the depth of the audience's immersion and be more superficial, although attention may be high. There will be changes in content, and therefore, the volatility of the cultural market will increase.

The ARIMA(2,1,2)-GARCH(1,1) model has a relatively low mean absolute percentage error (below 7%), and thus, the high-frequency cultural time series can be predicted by this econometric method to a certain extent that is practically applicable to the industry. Based on the above model, content distributors can optimise marketing expenses and time-limited promotions in accordance with the anticipated peak-demand period. The operator can use it to control the load of servers and content-moderation resources. The Office for Cultural Strategy can use this data to know the general situation and cultural diversity of the country at any time.

The three theoretical contributions of this paper are as follows: It extends media studies with econometrics. Media economics and cultural studies have been extended beyond the scope of description and correlation by a new formal time-series method. By showing that the ARIMA GARCH and Granger causality frameworks can be applied to cultural consumption data, we open a new path for combining financial econometrics and cultural analytics in an unexploited way. A modified Bass model can be used to quantify the extent of algorithmic promotion for platform studies and applied to various platform architectures and types of content. This paper takes algorithmic power as an example to measure the impact of all kinds of platforms, regulatory systems and types of content on dissemination. Time series econometrics has also been applied to short-video cultural data, and this has shown that the above methods are suitable for non-financial, high-frequency social media data. Given the good predictive performance, it can be inferred that the random processes of cultural attention are not fundamentally different from those in financial markets, thus providing a basis for cross-fertilisation.

The five-stage life cycle model and the forecast system are feasible means for content creators and distributors to organise promotional activities. Video Volume and User Engagement have been identified as the leading indicators; thus, pre-release content seeding and early optimisation of user engagement are expected to be the necessary conditions for hotspot formation. Producers need to create a considerable amount of initial content and design engagement triggers in the incubation period that can be promoted by algorithms. Given that platform operators have identified volatility clustering, algorithmic intervention during the incubation stage of an epidemic may be more effective than reactive promotion during an outbreak when volatility is already high and the additional impact of further algorithmic boosting is diminishing. A platform's early warning system will be used to identify incubating content with a high breakout risk for prompt adjustment of algorithm curation.

Policymakers for culture need to address regulatory problems, such as concentrated cultural attention and the risk of algorithmic amplification, to reduce the diversity of cultural consumption under the accelerated influence of algorithms. If the algorithms systematically promote the spread of certain types of content and suppress others, the cultural public sphere will become more and more uniform, and only the popular texts will gain attention at the expense of niche or alternative works. The government can establish standards for the openness of algorithm-based recommendation systems and promote an all-weather content system that does not rely solely on algorithms.

Some limitations of the generalisability and scope of the results have been identified. First, the dataset is limited to a single platform and a single calendar year; therefore, its generalizability to other platforms, such as Kuaishou, TikTok Global or YouTube Shorts, or to different periods under different macroeconomic or cultural circumstances, cannot be guaranteed. Second, although the Hotspot Index is all-encompassing, it is still a platform-centric indicator that does not include off-platform cultural impact indicators, such as box office performance, critical reviews by traditional media, or scholarly citations. Third, the Granger causality framework only shows temporal precedence but not structural causation; endogeneity problems still exist, such as the simultaneous determination of engagement and hotspot intensity.

The Three Directions for future research are: First, cross-platform comparison studies can rule out the effect of platform-specific algorithms on general diffusion dynamics to determine whether particular features of the platform architecture strongly influence the path of hotspots. Second, by incorporating textual and visual deep learning features of clip aesthetics, narrative structure and emotional valence into the time series model, both predictive accuracy and content-level determinants of virality can be improved. Thirdly, structurally constrained vector autoregression models with theoretically motivated identification restrictions can provide stronger causal inference than the reduced-form Granger approach employed here, and endogeneity may be addressed by adding exclusion restrictions based on institutional knowledge of platform operation.

The short-video ecosystem has created a new sense of time for cultural production and consumption, characterised by speed, fluctuation and algorithm-based organisation. The tools of time series econometrics can be applied to the structural features of platform media in this study to reveal the endogenous dynamics of cultural hotspots accurately and predict them effectively. As the film and television industry is increasingly carried by the algorithms of short-video platforms, we need to be able to model, predict and respond strategically to changes in "hotspot" trends. The framework proposed in this paper will provide strong support for our research and connect the methodological ideas of econometrics with real problems in media and culture in an advantageous way.

References

1. Bass, F. M. 1969. A new product growth for model consumer durables. Management Science 15, no. 5: 215–227.
2. Bollerslev, T. 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, no. 3: 307–327.
3. Box, G. E. P., and G. M. Jenkins. 1976. Time series analysis: Forecasting and control. San Francisco: Holden-Day.
4. Bucher, T. 2018. If...then: Algorithmic power and politics. New York: Oxford University Press.
5. Cunningham, S., and D. Craig. 2019. Social media entertainment: The new intersection of Hollywood and Silicon Valley. New Media & Society 21, no. 4: 1–18.
6. Dickey, D. A., and W. A. Fuller. 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74, no. 366: 427–431.
7. Granger, C. W. J. 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37, no. 3: 424–438.
8. Jenkins, H. 2006. Convergence culture: Where old and new media collide. New York: NYU Press.
9. Jin, D. Y. 2021. Artificial intelligence in cultural production: Critical perspectives on digital platforms. London: Routledge.
10. Lotan, G., E. Graeff, M. Ananny, D. Gaffney, I. Pearce, and D. Boyd. 2011. The revolutions were tweeted: Information flows during the 2011 Tunisian and Egyptian revolutions. International Journal of Communication 5: 1375–1405.
11. Napoli, P. M. 2019. Social media and the public interest: Media regulation in the disinformation age. New York: Columbia University Press.
12. Poell, T., D. Nieborg, and J. van Dijck. 2022. Platforms and cultural production. Cambridge: Polity Press.
13. Vosoughi, S., D. Roy, and S. Aral. 2018. The spread of true and false news online. Science 359, no. 6380: 1146–1151.
14. Zhang, X., and G. de Seta. 2021. Building platforms on content creators: A longitudinal analysis of Douyin's infrastructuralization of short video entertainment in China. Chinese Journal of Communication 14, no. 4: 398–417.

Author's Profile

Mengyao Qi (born February 1990) is a female scholar of Han ethnicity, native of Qingdao, Shandong Province. She is currently a doctoral candidate at the School of Humanities and Social Sciences, National University of Malaysia, and holds an associate professor position at the School of Journalism and Communication, Qingdao Film Academy. Her research focus lies in communication studies.

Shahrul Nazmi Bin Sannusi is an associate professor at the Centre for Media and Communication Studies (MENTION), Universiti Kebangsaan Malaysia (UKM). He received his Bachelor's and Master's degrees in Communication from Universiti Sains Malaysia and his Ph.D. from the University of Malaya. His research focuses on journalism studies, media and communication, crisis communication, corporate communication, media bias, and digital media. He has published widely in national and international journals indexed in Scopus and Web of Science.

Ammar Redza Bin Ahmad Rizal is a Senior Lecturer at the Centre for Media and Communication Studies (MENTION), Universiti Kebangsaan Malaysia (UKM). His research focuses on communication for behavioural change, innovation diffusion, strategic communication, and social transformation. His recent work explores ethical artificial intelligence in education, game-based learning for sustainability, persuasive communication, youth political engagement, and digital media communication. He has published in internationally recognized journals, including Environmental Communication, The Extractive Industries and Society, Sustainability, SAGE Open, Cogent Food & Agriculture, and Review of Communication Research. His current research interests include communication for social change, sustainability communication, digital storytelling, and the societal implications of emerging media technologies.